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Bhowmick et al.

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(54) **PRIVATE FEDERATED LEARNING WITH PROTECTION AGAINST RECONSTRUCTION**

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Related U.S. Application Data

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(51) **Int. Cl.**

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G06N 3/04	(2023.01)
G06N 5/04	(2023.01)
G06N 20/20	(2019.01)

(52) **U.S. Cl.**
CPC ***G06N 20/20*** (2019.01); ***G06N 3/04*** (2013.01); ***G06N 5/04*** (2013.01)

(58) **Field of Classification Search**
CPC G06N 20/20; G06N 3/04; G06N 5/04
USPC 706/12
See application file for complete search history.

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(57) **ABSTRACT**

Embodiments described herein provide for a non-transitory machine-readable medium storing instructions to cause one or more processors to perform operations comprising receiving a machine learning model from a server at a client device, training the machine learning model using local data at the client device, generating an update for the machine learning model, the update including a weight vector that represents a difference between the received machine learning model and the trained machine learning model, privatizing the update for the machine learning model, and transmitting the privatized update for the machine learning model to the server.

30 Claims, 11 Drawing Sheets

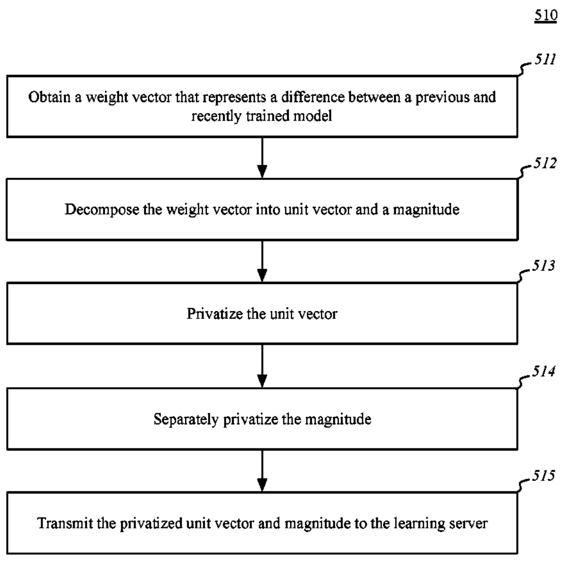
510
511
Obtain a weight vector that represents a difference between a previous and recently trained model
512
Decompose the weight vector into unit vector and a magnitude
513
Privatize the unit vector
514
Separately privatize the magnitude
515
Transmit the privatized unit vector and magnitude to the learning server

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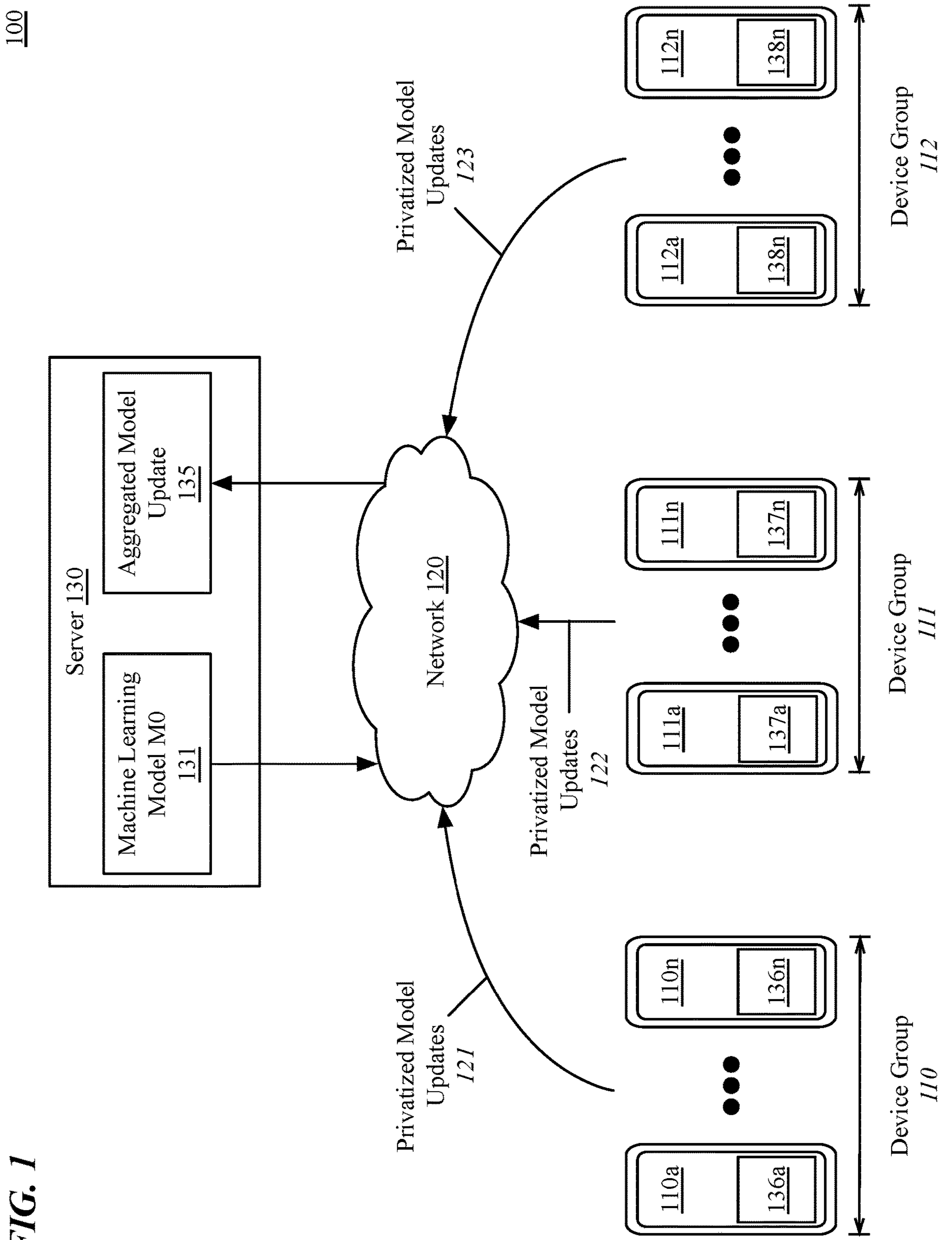
FIG. 1


100
Server 130
Machine Learning Model M0 131
Aggregated Model Update 135
Network 120
Privatized Model Updates 121
Privatized Model Updates 122
Privatized Model Updates 123
110a
136a
110n
136n
111a
137a
111n
137n
112a
138n
112n
138n
Device Group 110
Device Group 111
Device Group 112

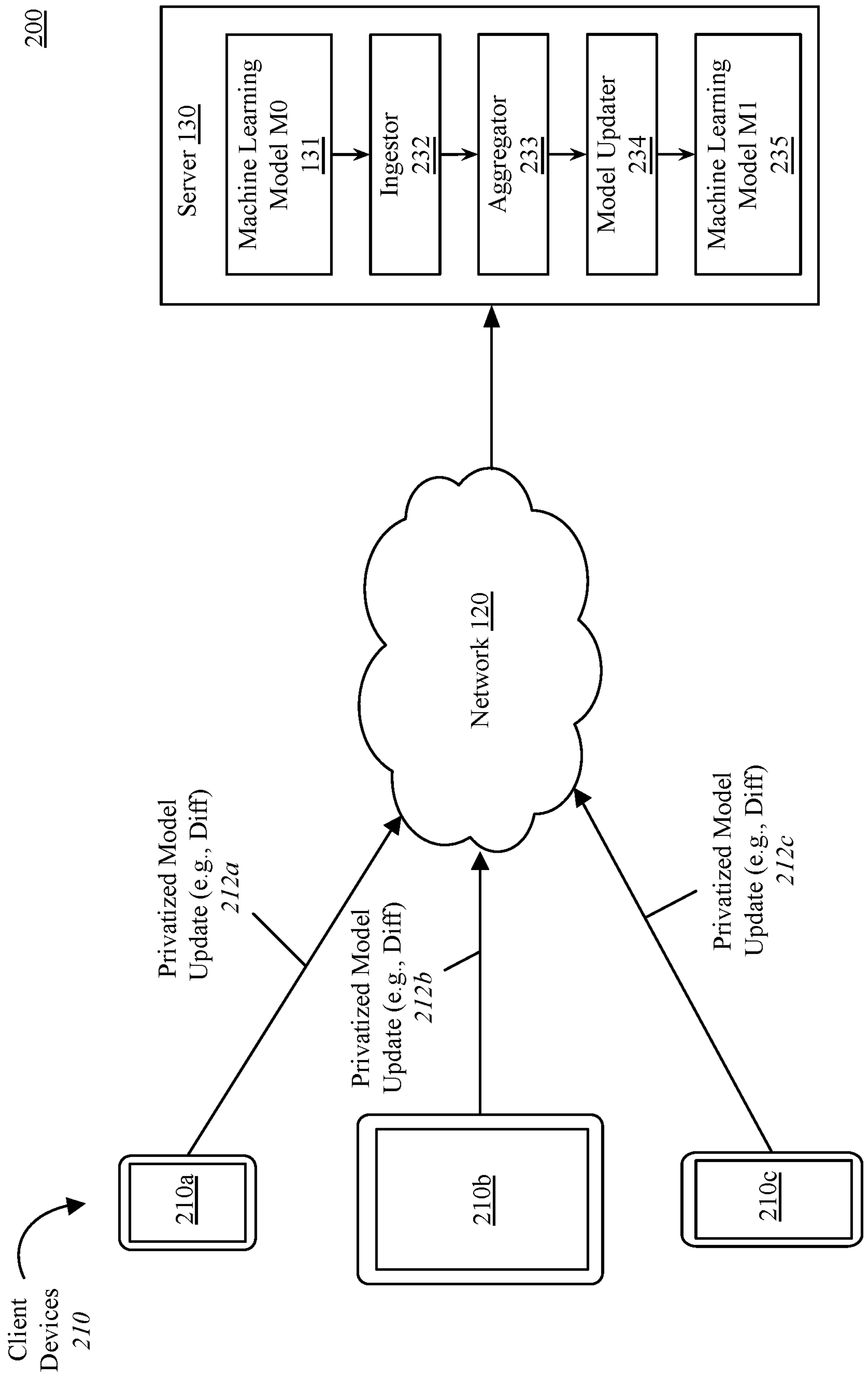

200
Server 130
Machine Learning Model M0 131
Ingestor 232
Aggregator 233
Model Updater 234
Machine Learning Model M1 235
Network 120
Privatized Model Update (e.g., Diff) 212a
Privatized Model Update (e.g., Diff) 212b
Privatized Model Update (e.g., Diff) 212c
Client Devices 210
210a
210b
210c

FIG. 2

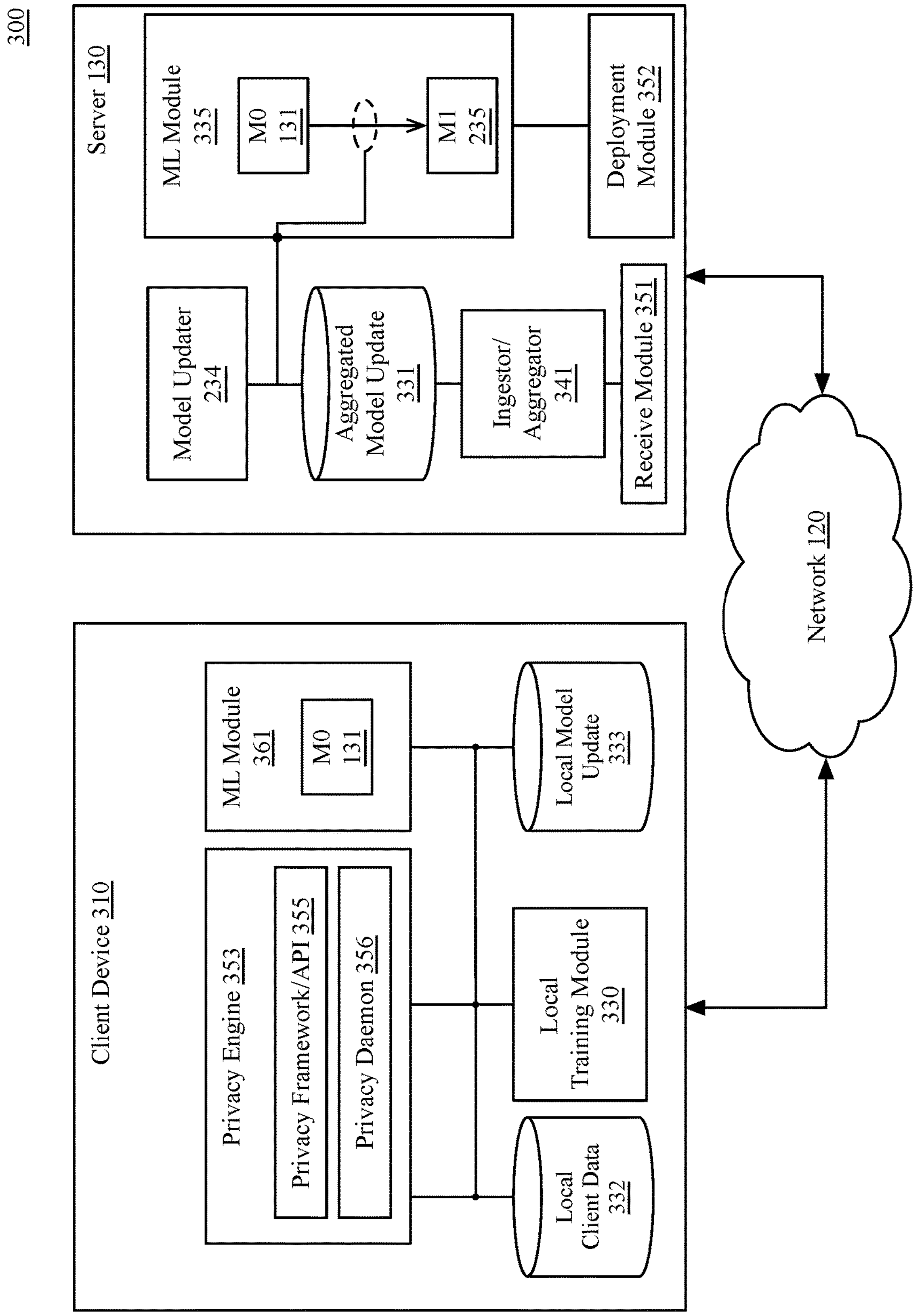

300
Server 130
ML Module 335
M0 131
M1 235
Deployment Module 352
Model Updater 234
Aggregated Model Update 331
Ingestor/ Aggregator 341
Receive Module 351
Network 120
Client Device 310
ML Module 361
M0 131
Local Model Update 333
Privacy Engine 353
Privacy Framework/API 355
Privacy Daemon 356
Local Training Module 330
Local Client Data 332

FIG. 3

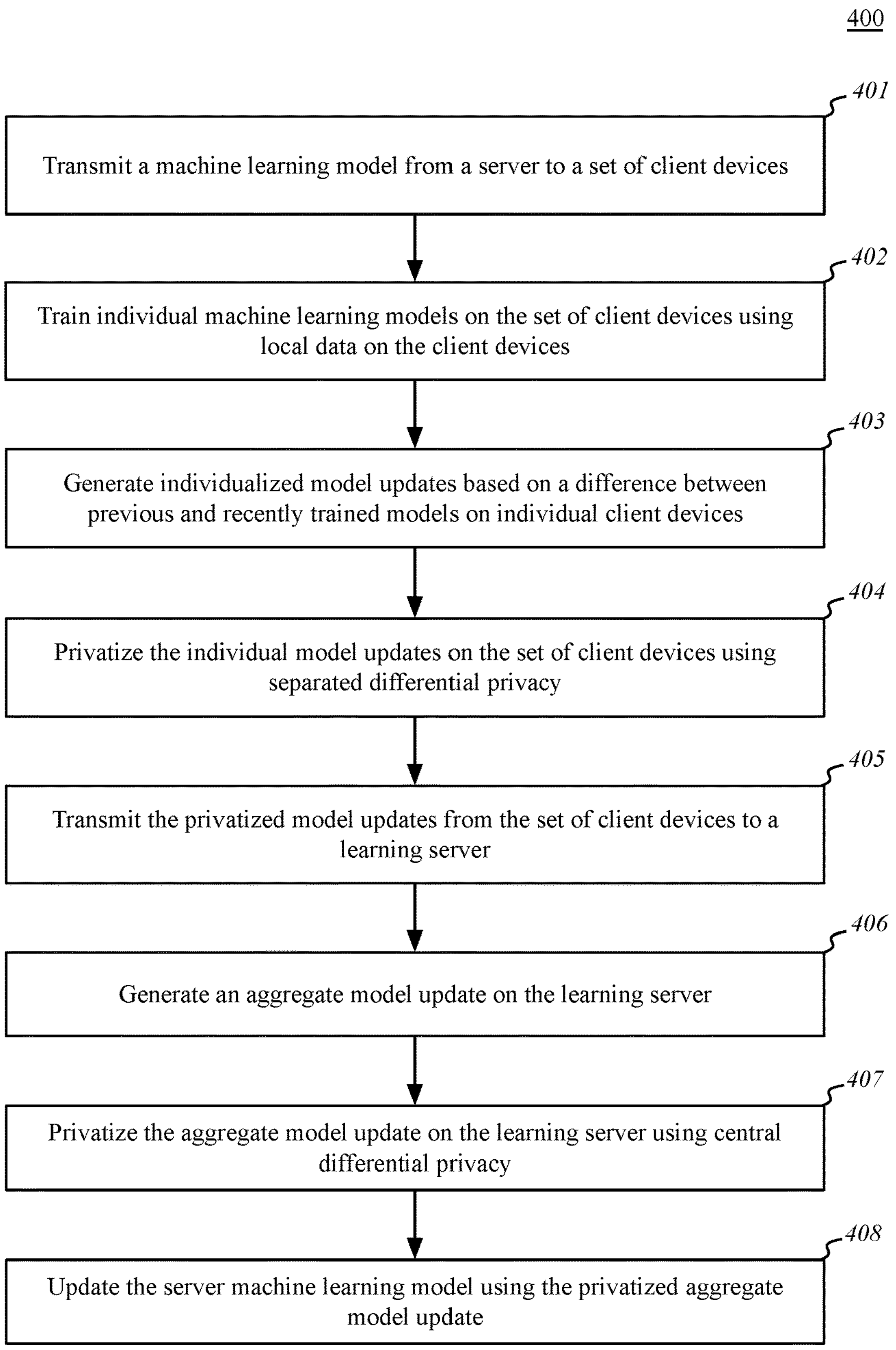

400
401
Transmit a machine learning model from a server to a set of client devices
402
Train individual machine learning models on the set of client devices using local data on the client devices
403
Generate individualized model updates based on a difference between previous and recently trained models on individual client devices
404
Privatize the individual model updates on the set of client devices using separated differential privacy
405
Transmit the privatized model updates from the set of client devices to a learning server
406
Generate an aggregate model update on the learning server
407
Privatize the aggregate model update on the learning server using central differential privacy
408
Update the server machine learning model using the privatized aggregate model update

FIG. 4

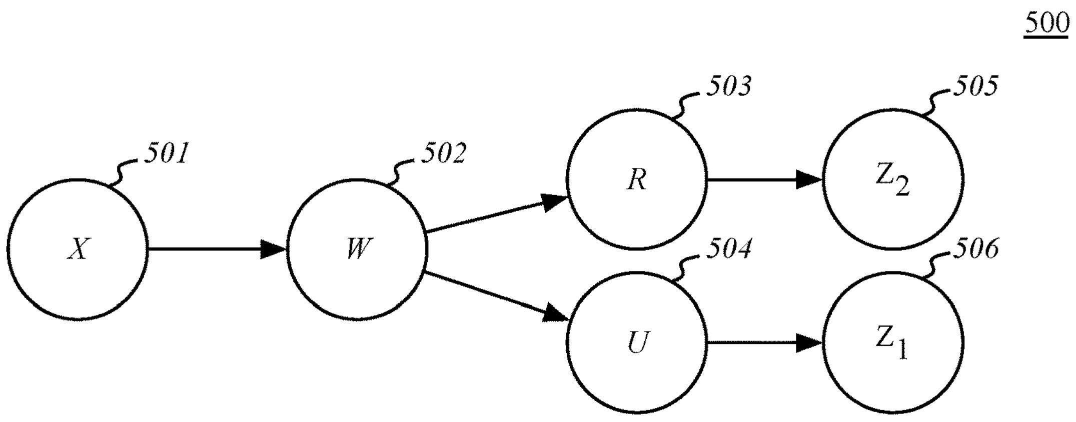

500
501
502
503
504
505
506
X
W
R
U
Z2
Z1

FIG. 5A

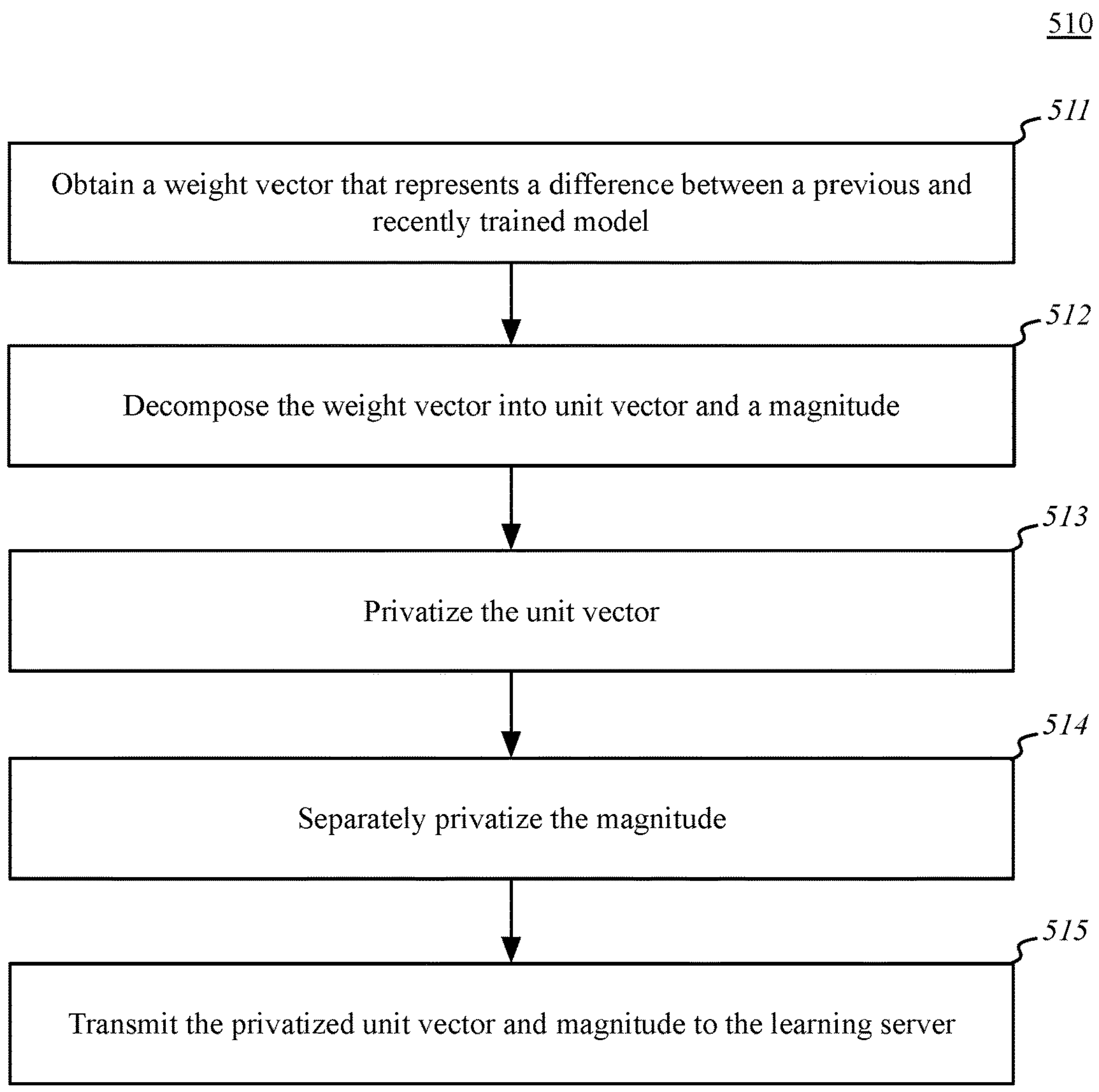

510
511
Obtain a weight vector that represents a difference between a previous and recently trained model
512
Decompose the weight vector into unit vector and a magnitude
513
Privatize the unit vector
514
Separately privatize the magnitude
515
Transmit the privatized unit vector and magnitude to the learning server

FIG. 5B

601

Privatized Unit Vector: `PrivUnit`$_2$

Given: $u \in \mathbb{S}^{d-1}, \gamma \in [0,1], \varepsilon' \geq 0$.

Draw random vector V according to the following distribution,

$$V = \begin{cases} \text{uniform on } \{v \in \mathbb{S}^{d-1} \mid \langle v, u \rangle \geq \gamma\} & \text{with probability } \frac{e^{\varepsilon'}}{1+e^{\varepsilon'}} \\ \text{uniform on } \{v \in \mathbb{S}^{d-1} \mid \langle v, u \rangle < \gamma\} & \text{otherwise.} \end{cases}$$

Set $\alpha = \frac{d-1}{2}$, $\tau = \frac{1+\gamma}{2}$

Set m to be the following value

$$m = \frac{(1-\gamma^2)^{\alpha}}{2^{d-2}(d-1)(1+e^{\varepsilon'})}\left[\frac{e^{\varepsilon'}}{B(\alpha,\alpha) - B(\tau;\alpha,\alpha)} - \frac{1}{B(\tau;\alpha,\alpha)}\right]$$

Set $Z = \frac{1}{m} \cdot V$

Transmit: Z

602

Privatized Unit Vector: `PrivUnit`$_\infty$

Given: $u \in \mathbb{H}^d$, $\kappa \in \{0, \cdots, d-1\}$, $\varepsilon' \geq 0$.

Round each coordinate of $u = (u_1, \cdots, u_d)$ to a corner of $\mathbb{H}^d$

for $j \in [d]$ **do**

$$\widehat{U}_j = \begin{cases} 1 & \text{w.p. } \frac{1+u_j}{2} \\ -1 & \text{else} \end{cases}$$

Draw random vector V according to the following distribution,

$$V = \begin{cases} \text{uniform on } \{v \in \{-1,+1\}^d \mid \langle v, \widehat{U} \rangle > \kappa\} & \text{with probability } \frac{e^{\varepsilon'}}{e^{\varepsilon}+1} \\ \text{uniform on } \{v \in \{-1,+1\}^d \mid \langle v, \widehat{U} \rangle \leq \kappa\} & \text{otherwise.} \end{cases}$$

Set $\tau = \frac{\lceil \frac{d+\kappa+1}{2} \rceil}{d}$

Debias the vector

$$m = \frac{1}{e^{\varepsilon'}+1} \cdot \left(\frac{e^{\varepsilon'}\binom{d-1}{d\tau-1}}{\sum_{\ell=\tau \cdot d}^{d}\binom{d}{\ell}} - \frac{\binom{d-1}{d\tau-1}}{\sum_{\ell=0}^{d\tau-1}\binom{d}{\ell}} \right)$$

Set $Z = \frac{1}{m} \cdot V$

Transmit: Z

603

Privatized magnitude: `PrivMagn`

Given: r magnitude, $\nu > 0$

Sample $Y \sim \mathsf{Uni}[-\nu, \nu]$

Set X $= 2\nu \cdot \frac{\exp(Y)}{\exp(\nu)-\exp(-\nu)}$

Transmit: r $\cdot X$

FIG. 6A

604

```
Privatize the magnitude with absolute error: AbsMagnDP
Given: Magnitude $r$, privacy parameter $\varepsilon > 0$, integer $k$, bound $r_{\max}$
    $r \leftarrow \min\{r, r_{\max}\}$
    Sample $J \in \{0, 1, \cdots, k\}$ such that
        $J = \begin{cases} \lfloor kr/r_{\max} \rfloor & \text{w.p. } (\lceil kr/r_{\max} \rceil - kr/r_{\max}) \\ \lceil kr/r_{\max} \rceil & \text{otherwise} \end{cases}$
    where $0/0$ is interpreted as 1.
    Use randomized response to obtain $\widehat{J}$
        $\widehat{J} \mid (J = i) = \begin{cases} i & \text{w.p. } \frac{e^{\varepsilon}}{e^{\varepsilon}+k} \\ \text{uniform in } \{0, \ldots, k\} \setminus i & \text{w.p. } \frac{k}{e^{\varepsilon}+k}. \end{cases}$
    Debias $\widehat{J}$, by setting
        $Z = a\left(\widehat{J} - b\right) \quad \text{for } a = \left(\frac{e^{\varepsilon}+k}{e^{\varepsilon}-1}\right)\frac{r_{\max}}{k} \quad \text{and} \quad b = \frac{k(k+1)}{2(e^{\varepsilon}+k)}.$
Transmit: $Z$
```

605

```
Privatize the magnitude with relative error: RelMagnDP
Given: Magnitude $r$, privacy parameter $\varepsilon > 0$, integer $k$, accuracy $\alpha, \nu > 1$, bound $r_{\max}$.
    $r \leftarrow \min\{r, r_{\max}\}$
    Form the intervals $\{E_0, E_1, \cdots, E_{k-1}\}$ and let $i^*$ be the index such that $r \in E_{i^*}$.
    Sample $J \in \{0, 1, \cdots, k\}$ such that
        $J = \begin{cases} 0 & \text{w.p. } \frac{\nu\alpha - r}{\nu\alpha} \\ 1 & \text{w.p. } \frac{r}{\nu\alpha} \end{cases} \text{ if } i^* = 0 \quad \text{and} \quad J = \begin{cases} i^* & \text{w.p. } \frac{\nu^{i^*+1}\alpha - r}{\nu^{i^*}(\nu-1)\alpha} \\ i^*+1 & \text{w.p. } \frac{r - \nu^{i^*}\alpha}{\nu^{i^*}(\nu-1)\alpha} \end{cases} \text{ if } i^* \geq 1.$
    Use randomized response to obtain $\widehat{J}$
        $\widehat{J} \mid (J = i) = \begin{cases} i & \text{w.p. } \frac{e^{\varepsilon}}{e^{\varepsilon}+k} \\ \text{uniform in } \{0, \ldots, k\} \setminus i & \text{w.p. } \frac{k}{e^{\varepsilon}+k}. \end{cases}$
    Set $\tilde{J} = \nu^{\hat{J}} \cdot \mathbb{1}\left\{\hat{J} \geq 1\right\}$
    Debias $\tilde{J}$, by setting
        $Z = a\left(\tilde{J} - b\right) \quad \text{for } a = \alpha \cdot \left(\frac{e^{\varepsilon}+k}{e^{\varepsilon}-1}\right) \quad \text{and} \quad b = \frac{1}{e^{\varepsilon}+k} \cdot \sum_{j=1}^{k} \nu^{j}.$
Transmit: $Z$
```

FIG. 6B

606

Efficient Sampling of unit vectors in **PrivUnit$_2$**

```
**Given:** $u \in \mathbb{S}^{d\ \ 1}$ and $\gamma \in [0, 1]$.
  Sample $\mathrm{Y} = \mathrm{Bern}\left(\frac{e^{\varepsilon'}}{e^{\varepsilon}+1}\right)$
  if $\mathrm{Y} = 1$ **then**
      Sample $B' = 2B - 1$ where $B \sim \mathsf{Beta}\left(\frac{d-1}{2}, \frac{d-1}{2}\right)$ conditioned on $B \geq \frac{\gamma+1}{2}$
      Set $\widehat{U} \quad B' \cdot u$
      Draw $U \sim \mathsf{Uni}(\mathbb{S}^{d-1})$. # Can do this by sampling a $d$ standard gaussians and then normalizing.
      Set $V \quad \sqrt{1 - B'^2} \cdot \frac{(I - uu^\intercal)U}{\|(I_d - uu^\intercal) \cdot U\|_2}$
      Set $V \leftarrow \widehat{U} + V$
  **else**
      Do rejection sampling, i.e.
      $\mathsf{Bool} \leftarrow$ True
      **while** $\mathsf{Bool}$ **do**
          Draw $U \sim \mathsf{Uni}(\mathbb{S}^{d-1})$.
          **if** $\langle U, u \rangle < \gamma$ **then**
              $V \leftarrow U$
              $\mathsf{Bool} =$ False
**Provide:** $V$
```

FIG. 6C

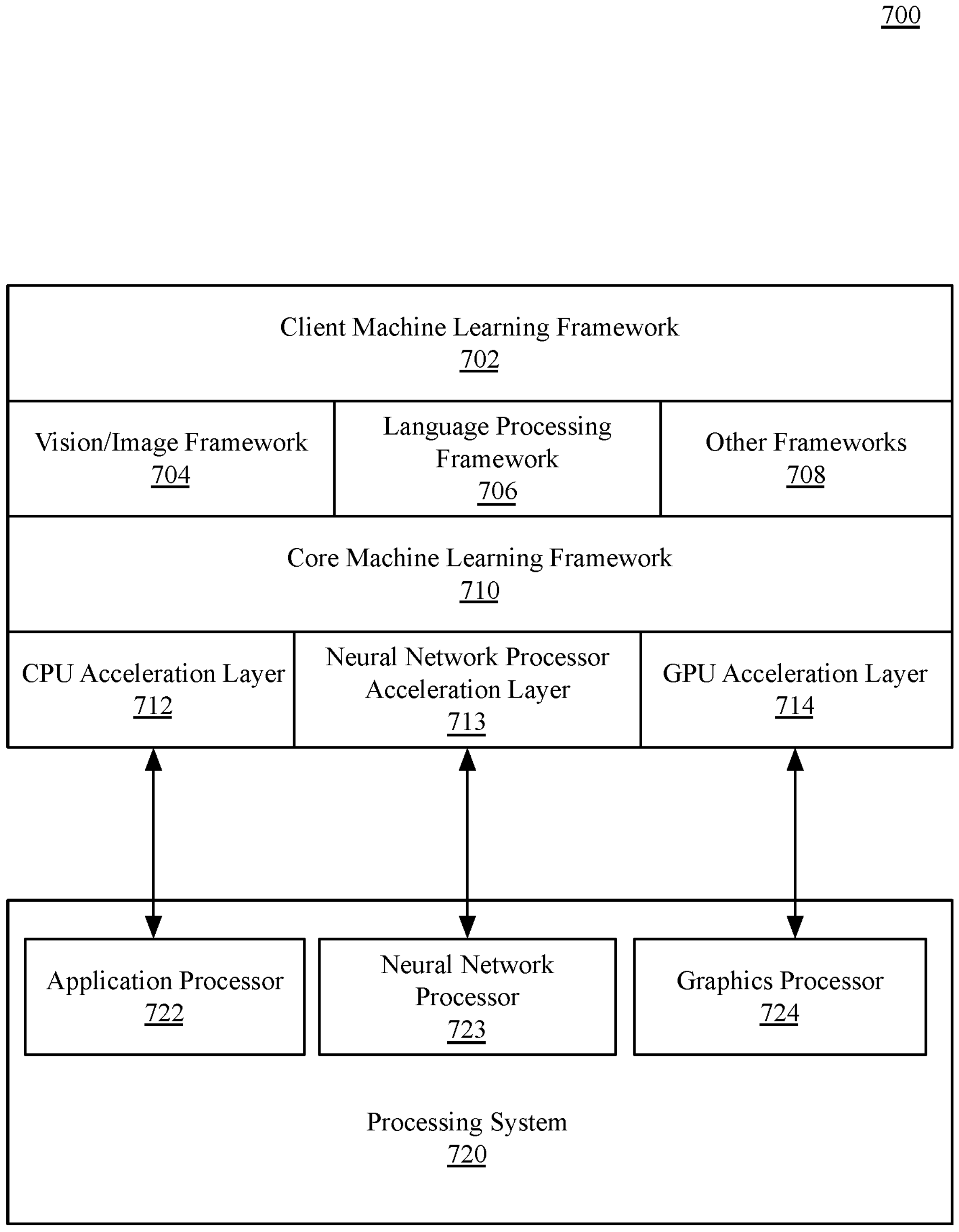

700
Client Machine Learning Framework
702
Vision/Image Framework
704
Language Processing Framework
706
Other Frameworks
708
Core Machine Learning Framework
710
CPU Acceleration Layer
712
Neural Network Processor Acceleration Layer
713
GPU Acceleration Layer
714
Application Processor
722
Neural Network Processor
723
Graphics Processor
724
Processing System
720

FIG. 7

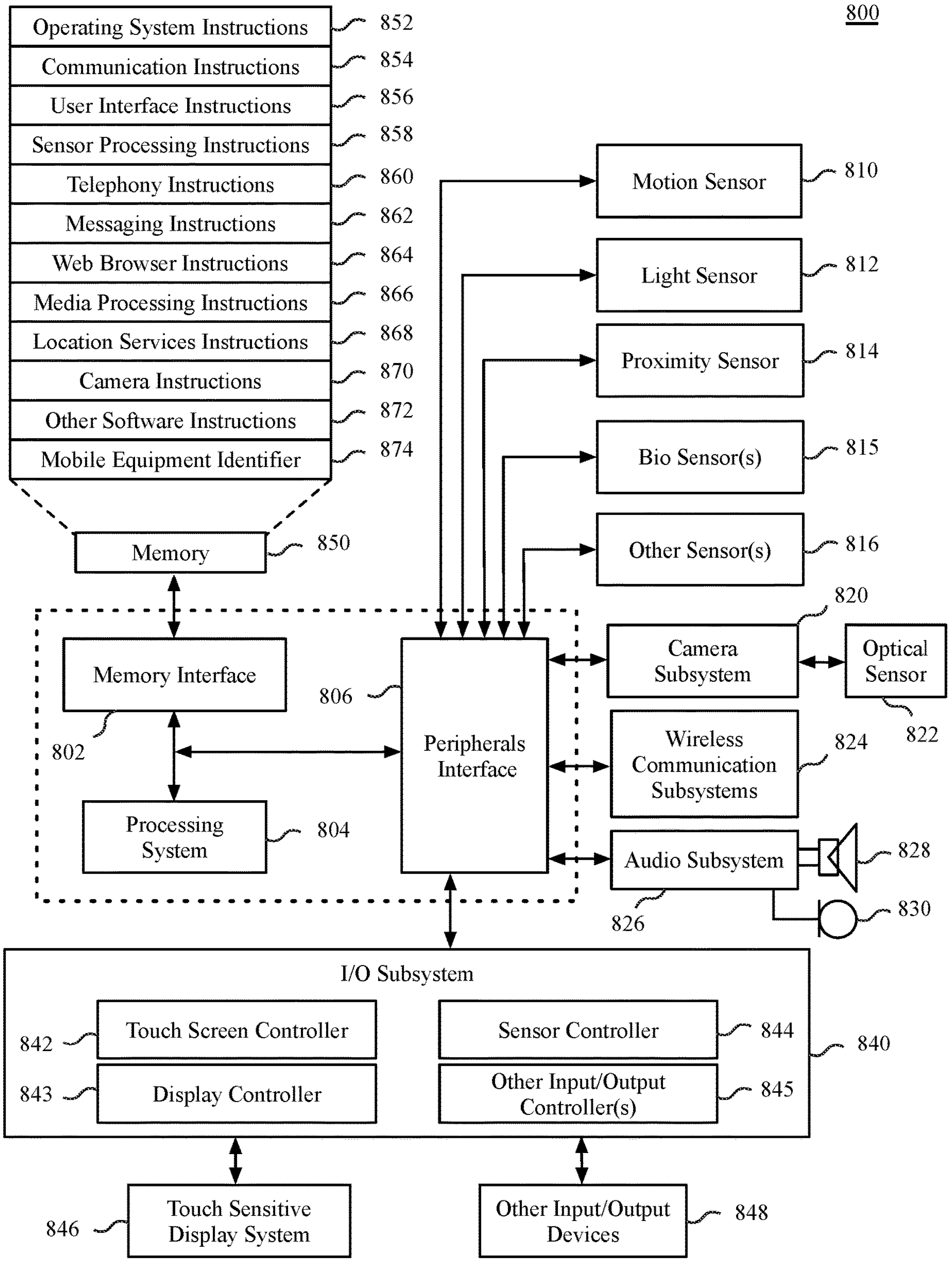

800
Operating System Instructions
852
Communication Instructions
854
User Interface Instructions
856
Sensor Processing Instructions
858
Telephony Instructions
860
Messaging Instructions
862
Web Browser Instructions
864
Media Processing Instructions
866
Location Services Instructions
868
Camera Instructions
870
Other Software Instructions
872
Mobile Equipment Identifier
874
Memory
850
Motion Sensor
810
Light Sensor
812
Proximity Sensor
814
Bio Sensor(s)
815
Other Sensor(s)
816
820
Camera Subsystem
Optical Sensor
822
Memory Interface
802
806
Peripherals Interface
Processing System
804
Wireless Communication Subsystems
824
Audio Subsystem
826
828
830
I/O Subsystem
842
Touch Screen Controller
843
Display Controller
Sensor Controller
844
Other Input/Output Controller(s)
845
840
846
Touch Sensitive Display System
Other Input/Output Devices
848

FIG. 8

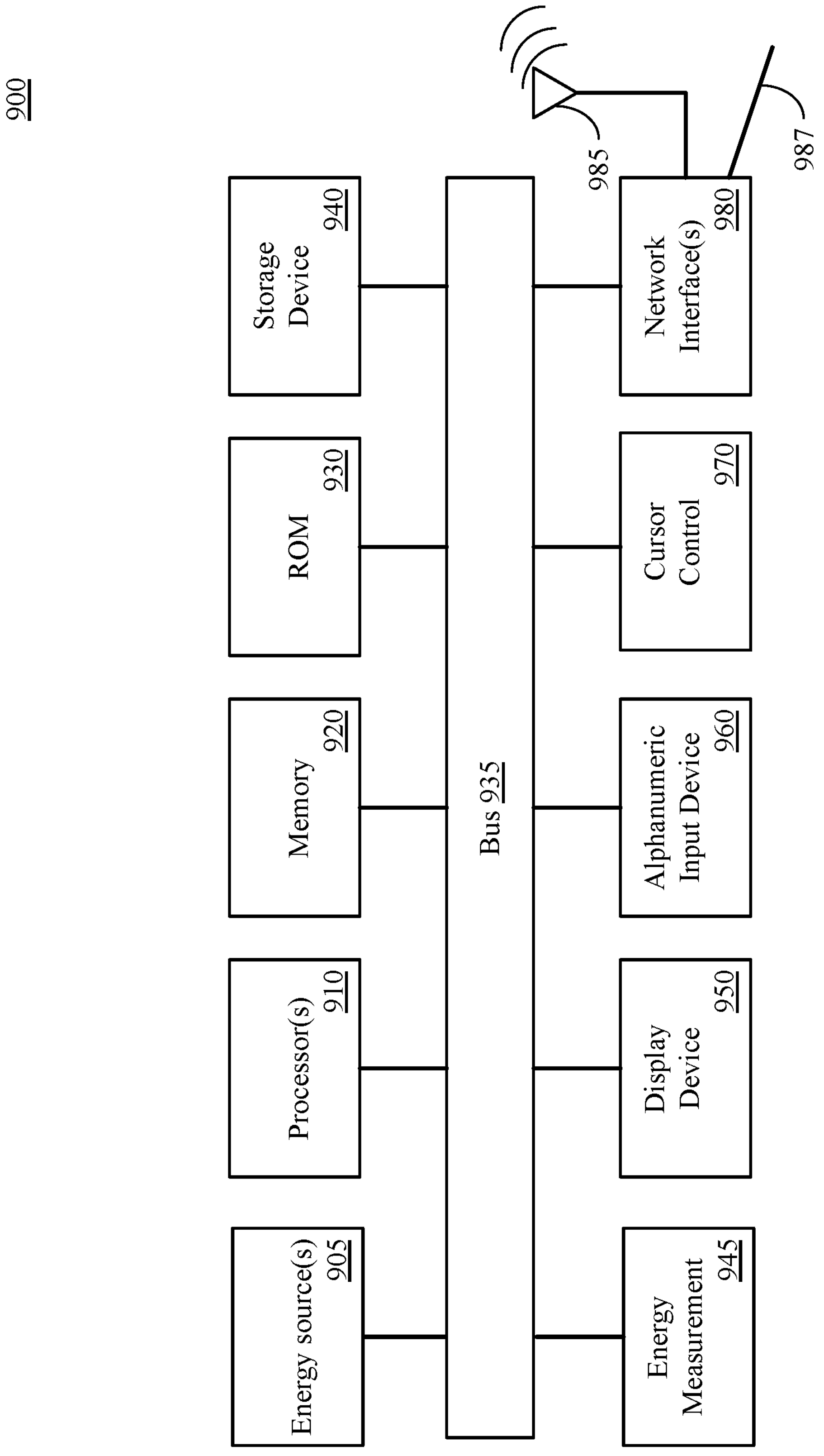

900
Energy source(s) 905
Processor(s) 910
Memory 920
ROM 930
Storage Device 940
Bus 935
Energy Measurement 945
Display Device 950
Alphanumeric Input Device 960
Cursor Control 970
Network Interface(s) 980
985
987

FIG. 9

PRIVATE FEDERATED LEARNING WITH PROTECTION AGAINST RECONSTRUCTION

RELATED APPLICATIONS

This application claims the benefit of priority of U.S. Provisional Application No. 62/774,126, filed Nov. 30, 2018 and U.S. Provisional Application No. 62/774,227, filed Dec. 1, 2018, each of which is herein incorporated by reference in their entirety.

FIELD

Embodiments described herein relate generally to federated machine learning using distributed computing systems. More specifically, embodiments relate to a private federated learning system with protections against reconstruction attacks.

BACKGROUND OF THE DESCRIPTION

The training of machine learning models for use in image classification, next word prediction, and other related tasks generally makes use of powerful hardware and a large amount of data. The large amount of training data can increase the accuracy of the trained models. The more powerful the hardware, the faster the training operations can be performed. Previously, the training of machine learning models required dedicated, high-performance compute nodes. However, modern mobile electronic devices are now able to perform on-device training, even for large complex machine learning models. Training data can be divided and distributed to a large number of mobile electronic devices, which can each perform on-device training of the model using a subset of the training data. However, the training data that is used on each mobile device is generally a small fraction of the full dataset.

Computing a shared model that leverages the full dataset would significantly outperform each of the individual models trained on its own dataset. Shared models can then be deployed to each device to benefit all users for a variety of tasks, which can improve the overall user experience. One way to compute a shared model in this distributed setting is to directly transmit data from each device to a central server where training can be done. However, the data on each device is sensitive by nature and transmitting user data to a centralized server can compromise the privacy of user data.

SUMMARY OF THE DESCRIPTION

Various embodiments of a private federated learning system with protections against reconstruction attacks will be described herein.

One embodiment provides for a data processing system comprising a memory to store instructions and one or more processors to execute the instructions. The instructions cause the one or more processors to receive a machine learning model from a server at a client device, train the machine learning model using local data at the client device to generate a trained machine learning model, generate an update for the machine learning model, the update including a weight vector that represents a difference between the machine learning model and the trained machine learning model, privatize the update for the machine learning model, and transmit the privatized update for the machine learning model to the server.

One embodiment provides for a method comprising receiving a machine learning model from a server at a client device, training the machine learning model using local data at the client device to generate a trained machine learning model, generating an update for the machine learning model, the update including a weight vector that represents a difference between the machine learning model and the trained machine learning model, privatizing the update for the machine learning model, and transmitting the privatized update for the machine learning model to the server.

One embodiment provides for a non-transitory machine-readable medium that stores instructions to cause one or more processors of a data processing system to perform operations comprising receiving a machine learning model from a server at a client device, training the machine learning model using local data at the client device, generating an update for the machine learning model, the update including a weight vector that represents a difference between the received machine learning model and the trained machine learning model, privatizing the update for the machine learning model, and transmitting the privatized update for the machine learning model to the server.

In embodiments described herein, privatizing the update for the machine learning model can be performed using a variety of mechanisms, including the use of a separated differential privacy mechanism that separately privatizes a unit vector and a magnitude for each update to the machine learning model before the update is transmitted by the user device. Privatizing the update using separated differential privacy includes decomposing the weight vector into a unit vector and a magnitude, privatizing the unit vector, and separately privatizing the magnitude. In one embodiment the magnitude is privatized with absolute error. In one embodiment the magnitude is privatized with relative error. In one embodiment the unit vector is privatized based on ℓ_2-unit vectors on the unit cube. In one embodiment, the unit vector is privatized based on ℓ_∞-unit vectors on the unit cube.

Other features and advantages will be apparent from the accompanying drawings and from the detailed description.

BRIEF DESCRIPTION OF THE DRAWINGS

Various embodiments and aspects of a private federated learning system will be described herein, with reference to details discussed below. The described embodiments are illustrated by way of example and not limitation in the figures of the accompanying drawings, in which like references indicate similar elements, and in which:

FIG. **1** illustrates a system to enable private federated learning, according to an embodiment;

FIG. **2** illustrates an additional system to enable private federated learning, according to embodiments described herein;

FIG. **3** is a block diagram of a system for generating privatizing model updates, according to an embodiment;

FIG. **4** is a flow diagram of a method of performing private federated learning using the computing components and privatization techniques described herein;

FIG. **5**A-**5**B illustrates techniques for privatizing model updates, according to an embodiment;

FIG. **6**A-**6**C illustrate algorithms to generate a privatized unit vector and privatized magnitude, according to embodiments;

FIG. **7** illustrates compute architecture on a client device that can be used to enable on-device training using machine learning algorithms, according to embodiments described herein;

FIG. **8** is a block diagram of a device architecture for a mobile or embedded device, according to an embodiment; and

FIG. **9** is a block diagram of a computing system, according to an embodiment.

DETAILED DESCRIPTION

Federated learning, also referred to as distributed learning, focuses on learning problems when data is distributed across many devices. Let $\theta \in \Theta$ be model parameters for a particular model that is to be trained using user data. In federated learning, the model parameters θ are transmitted to each device and then each device trains a local model using its local data. The locally trained model on device i becomes θ_i and the difference between the starting model parameters and the locally trained parameters $\Delta_i = \theta_i - \theta$ are sent to a central server. A collection of b model differences $\{\Delta_1, \ldots, \Delta_b\}$ is then aggregated to obtain Δ on a central server which is then used to update the central model parameters $\theta \leftarrow \theta + \Delta$. The update to the shared model can then be deployed to the mobile devices. This feedback loop continues as the model improves and the user data changes.

Some approaches to federated learning, even when performing on-device training, does not provide any formal privacy guarantees to users that participate in the federated learning system. Even though data remains on device, the transmitted model updates are computed with user data and contain information about the personal data. A curious onlooker that has access to the model updates may be able to reconstruct data of individual users.

One approach for incorporating privacy into federated learning is to use differential privacy on the server, typically called the central model of differential privacy. Differential privacy has many nice properties, including closure under post-processing and the graceful degradation of privacy parameters if multiple differential privacy algorithms are composed together, that has made it the de facto privacy definition in data analytics and machine learning. However, an objection to differential privacy in the central model is that the users submit their data, perhaps through an encrypted channel, that is then decrypted on the server. Thus, the server is trusted to use a differential privacy algorithm with the data to only reveal a privatized result. An adversary with access to the server may be able to see the true model updates prior to any execution of a differential privacy algorithm.

Another approach to protecting the individual updates is to use secure multiparty computation (SMC). However, with SMC, the communication cost of a user scales with the number of users that are selected to submit updates. In this setting, it is assumed that users remain online for multiple rounds of communication, which may be unrealistic in practical settings. Further, the on-device computational difficulty scales linearly with the dimension of the model and the number of users contributing updates, which may be prohibitively expensive. An optimal approach would ensure privacy with minimal impact to computation cost on device and communication cost between the devices and the server.

Local privacy protections provide numerous benefits including avoiding risks associated to maintaining private data. Additionally, local privacy protections allow transparent protection of user privacy, as private data never leaves an individual's device in the clear. However, local differential privacy can create challenges for learning systems.

Embodiments described herein address the above deficiencies in the art by providing a private federated learning system that privatizes model updates submitted by users via a separated differential privacy model with protections against adversaries with some prior information about user updates. Separated differential privacy involves decomposing the weight vector that includes updates to a learning model into a unit vector and an associated magnitude. The decomposed vectors can then be separately privatized using techniques described herein. Separated differential privacy enables privatized learning by implementing a privacy model that is tailored towards protecting against an attacker that may wish to decode individual user data based on model updates, rather than an attacker that wants to differentiate between two inputs. This approach allows the use of a more relaxed privacy parameter ε, which improves the effectiveness of the learning process, while still providing protection against curious onlookers that may be able to obtain access to privatized model updates.

This model of privacy is well suited to federated learning scenarios that use distributed model training. Separated differential privacy enables learning models to be trained in a decentralized setting while providing local privacy guarantees for the transmitted model updates from the devices. Using separated differential privacy, a private federated learning system can be enabled that provides comparable utility to a federated learning system that does not provide privacy safeguards. Privacy is enabled by obfuscating the individual updates to the server. In one embodiment a relaxed privacy parameter ε is used, user data is still protected against reconstruction by individuals (e.g., internal employees) that may have access to privatized updates. In one embodiment, fully ε-differentially-private techniques are used to enable privatization of the magnitude. In another embodiment, relative noise mechanisms are used to privatize the magnitude.

In addition to separated differential privacy, an additional layer of privacy is enabled by encapsulating the separated differential privacy model within a central differential privacy layer on the learning server. The use of central differential privacy provides additional protection for updated learning models on the server against external adversaries that may have access to the model and any other information except the user data that the adversary wishes to decode.

In the description and figures, numerous specific details are described to provide a thorough understanding of various embodiments. However, in certain instances, well-known or conventional details are not described to provide a concise discussion of embodiments. Additionally, reference herein to "one embodiment" or "an embodiment" or "some embodiments" means that a particular feature, structure, or characteristic described in conjunction with the embodiment can be included in at least one embodiment. The appearances of the phrase "embodiment" in various places in the specification do not necessarily all refer to the same embodiment. It should be noted that there could be variations to the flow diagrams or the operations described therein without departing from the embodiments described herein. For instance, operations can be performed in parallel, simultaneously, or in a different order than illustrated.

FIG. **1** illustrates a system **100** to enable private federated learning, according to an embodiment. In one embodiment the system **100** includes a server **130** that can receive data from a set of client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n* over a network **120**. The server **130** can be any kind of server, including an individual server or a cluster of servers. The server **130** can also be or include a cloud-based server, application server, backend server, virtual server, or combination thereof. The network **120** can be any suitable type of wired or wireless network such as a local area network (LAN), a wide area network (WAN), or combination thereof. Each of the client devices can include any type of computing device such as a desktop computer, a tablet computer, a smartphone, a television set top box, a smart speaker system, a gaming system, or other computing device. For example, a client device can be an iPhone®, Apple® Watch, Apple® TV, HomePod™, etc., and can be associated with a user within a large set of users to which tasks can be crowd-sourced with the permission of the user.

In one embodiment, the server **130** stores a machine learning model 131 (e.g., model M0), which can be implemented using one or more neural networks, such as but not limited to a deep learning neural network. The machine learning model **131** can be implemented using, for example, a convolutional neural network (CNN) or a recurrent neural network (RNN), including a long short-term memory (LSTM) variant of an RNN. Other types of machine learning models and/or neural networks can be used. The machine learning model **131** can include a set of model weights that can be updated based on an aggregated model update **135** that is generated based on aggregated privatized model updates sent from the set of client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n*.

The client devices can be organized into device groups (e.g., device group **110**, device group **111**, device group **112**) that can each contain multiple client devices. Each device group can contain n devices, where n can be any number of devices. For example, device group **110** can contain client device **110***a*-**110***n*. Device group **111** can contain client device **111***a*-**111***n*. Device group **112** can contain client device **112***a*-**112***n*. In one embodiment, each device group can contain up to 128 devices, although the number of client devices in each device group can vary across embodiments and is not limited to any specific number of devices.

In one embodiment, each of the client devices (client device **110***a*-**110***n*, client device **111***a*-**111***n*, client device **112***a*-**112***n*) can include a local machine learning module. For example, client device **110***a*-**110***n* of device group **110** can each contain corresponding local machine learning module **136***a*-**136***n*. Client device **111***a*-**111***n* of device group **111** can each contain corresponding local machine learning module **137***a*-**137***n*. Client device **112***a*-**112***n* of device group **112** can each contain a corresponding local machine learning module **138***a*-**138***n*. In various embodiments, the local machine learning modules can be loaded on each client device during factory provisioning or can be loaded or updated when a system image of the client device is updated. In one embodiment, the machine learning model **131** of the server **130** can be transmitted to each local machine learning module over the network **120**. The local machine learning models on the client devices can be individualized to each client device by training the local models using local data stored on the client device. In one embodiment, different types of data can be used to train the models, and the specifics of the models can vary based on the type of data that is used to train. In one embodiment the machine learning model **131** and the local machine learning models are image classifier models. In one embodiment the models are natural language processing models that are used to enable a predictive keyboard and/or keyboard autocorrect. In one embodiment the models can be voice recognition or voice classification models that are used to improve voice recognition or voice classification capability for a virtual assistant.

The local machine learning modules **136***a*-**136***n*, **137***a*-**137***n*, **138***a*-**138***n* on each client device can generate model

updates that are privatized by the client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n* before transmission to the server **130**. For example, client devices **110***a*-**110***n* can each send privatized model updates **121**, client devices **111***a*-**111***n* can each send privatized model updates **122**, and client devices **112***a*-**112***n* can each send privatized model updates **123**. The privatized model updates can be sent through the network **120** to the server **130**, where the updates can be processed into an aggregated model update **135**. Updates are sent to the server while satisfying separated differential privacy for the local updates and no raw data for users is transmitted to the server. Separated differential privacy is used to protect the privatized model updates **121**, **22**, **123** from a reconstruction breach. A reconstruction breach occurs when a curious onlooker having access to the model updates is able to determine at least some detail about the user data on which the model is trained.

Consider the models updates as being a high dimensional vector $W \in \mathbb{R}^d$, which is the difference between the original model weights and the model weights after training with the local data X. The private federated learning system described herein is configured such that adversaries that can view the transmitted updates M(W)=Z (where $M: \mathbb{R}^d \rightarrow Z$ is some mechanism) cannot construct an estimator based on Z that can be close to W, or any target function f of W within some tolerance α.

FIG. **2** illustrates an additional system **200** to enable private federated learning, according to embodiments described herein. In one embodiment, the system **200** includes a set of client devices **210***a*-**210***c* (collectively, **210**), which can be any of the client devices described above (e.g., client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n*). The client devices **210**, using the techniques described above, can generate privatized model updates **212***a*-**212***c* (e.g., privatized model update **212***a* from client device **210***a*, privatized model update **212***b* from client device **210***b*, privatized model update **212***c* from client device **210***c*), which can be transmitted to the server **130** via the network **120**. The privatized model updates **212***a*-**212***c* can be stripped of their IP addresses or other information that can be used to identify the client devices **210** prior to entering an ingestor **232** on the server **130**. The ingestor **232** can collect the data from the client devices **210** and remove metadata and forwards the data to an aggregator **233**. The aggregator takes the privatized model updates and aggregates them to form a single update to the current server model, which in the initial round is machine learning model **131** (e.g., model M0). A model updater **234** can then apply the updates to the current server model to generate an updated machine learning model **235** (e.g., model M1). The privatized model updates **212***a*-**212***c* can be protected using separated differential privacy as described herein. The aggregated model updates and/or updated machine learning model **235** can be protected using the central model of differential privacy.

FIG. **3** is a block diagram of a system **300** for generating privatizing model updates, according to an embodiment. The system **300** includes a client device **310**, which can be any of client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n* or client devices **210**. The client device **310** includes a machine learning module **361** that includes, at least initially, a copy of machine learning model **131**, which can be provided by the server **130**. A local training module **330** can be used to train the machine learning model **131** based on local client data **332** to generate a local model update **333**. The local model update **333** is then privatized using a privacy engine **353**. In one embodiment the privacy engine **353** includes a privacy daemon **356** and a privacy framework or application programming interface (API) **355**. The privacy engine **353** can use various tools, such as hash functions, including cryptographic hash functions, to privatize the local model update **333** to the machine learning model **131** using one or more of a variety of privatization techniques including but not limited to separated differential privacy as described herein. The privatized local model update **333** can then be transmitted to the server **130** via the network **120**.

The server **130** can include a receive module **351** and an ingestor/aggregator **341**. The receive module **351** can asynchronously receive privatized model updates from a large plurality of client devices and provide the updates to the ingestor/aggregator **341**. The receive module **351** can remove latent identifiers such as IP addresses or other data that might identify the client device **310**. The ingestor/aggregator can include components of the ingestor **232** and aggregator **233** shown in FIG. **2** and can perform similar operations, such as removing metadata, session identifiers, and other identifying information, and aggregating the privatized information to generate an aggregated model update **331**. The aggregated model update **331** can be used by the model updater **234** to update machine learning model **131** (e.g., model M0) into updated machine learning model **235** (e.g., model M1). A deployment module **352** can then be used to deploy the updated machine learning model **235** to the client devices for an additional round of training. While the updated machine learning model **235** is on the server **130**, the model can be protected using central differential privacy.

FIG. **4** is a flow diagram of a method **400** of performing private federated learning using the computing components and privatization techniques described herein. Operations of the method **400** will be described below, along with relevant mathematical descriptions of the operations to be performed. The method **400** includes operations (block **401**) to transmit a machine learning model from a server to a set of client devices. Let $\theta \in \Theta$ be model parameters for a particular model that is to be trained using user data. The model parameters θ are transmitted to each device in a set of client devices. The server can be, for example, server **130** as described herein. The client devices can be, for example, client devices **110***a*-**110***n*, **111***a*-**111***n*, **112***a*-**112***n*, client devices **210**, or the client device **310** as described herein. Each client device then performs operations (block **402**) to train an individual machine learning model using local data on the client device. For example, the locally trained model on device i becomes θ_i and the difference between the starting model parameters and the locally trained parameters $\Delta_i = \theta_i - \theta$ are determined. Individualized model updates can be generated based on an individualized difference between a previous model (e.g., starting model, previous model iteration, etc.) and a most recent locally trained model on the individual client devices (block **403**). The individual model updates can then be privatized on the set of client devices using separated differential privacy (block **404**). The privatized model updates are then sent from the set of client devices to a central learning server (block **405**). A collection of b model differences $\{\Delta_1, \ldots, \Delta_b\}$ is then aggregated to obtain an aggregate model update Δ on the central server (block **406**). The aggregate model update can then be used to update the central model parameters $\theta \leftarrow \theta + \Delta$. The update to the shared model can then be deployed to the client devices. These operations can continue in a loop continues as the model improves and user data changes. In one embodiment, central differential privacy techniques are used to protect the model updates on the server. Method **400** can additionally include to privatize the aggregate model updates on the learning server using central differential privacy (block **407**). The privatized model updates can then be used to update the server machine learning model (block **408**). Additional details are provided below for the operations of method **400**.

With respect to the operations (block **401**) to transmit the machine learning model to the set of client devices, the server has some global model parameters $\theta \in \mathbb{R}^d$, which can be the model weights for each layer of a neural net or it can be the model weights of just the last layer in the case of transfer learning. Each model can have a particular neural net architecture and loss function, which in one embodiment are assumed to be consistent across devices. Each model also has some set of hyperparameters $\mathcal{H}$ which will include parameters such as learning rate, dropout rate, mini-batch size, number of rounds for training, trainable parameters, etc. These hyperparameters are tuned on the server and sent along with the current server model $\theta \in \mathbb{R}^d$, to each device. The server then sends the current model θ to a batch of devices, where each device will train the model using local data. The batch of devices will be of expected size $q \cdot N$ where N is the total number of users opted in for training and q is the subsampling rate, so that user i will be selected for local training with probability q. The selected batch can be denoted as $\mathcal{B} \subseteq [n]$.

With respect to the operations (block **402**) to perform on-device training, user data is leveraged to update central model parameters θ. Let user i have a dataset with n_i example-label pairs $x_i = \{x_{i,1}, \ldots, x_{i,n_i}\}$, each $i \in B$ performs

$$\theta_i \leftarrow \text{Update}(x_i, \theta; \mathcal{H})$$

where Update denotes the update rule on each device. Any update procedure can be used. A possible update rule includes Gradient Descent, where for learning rate $\eta \in \mathcal{H}$

$$\text{Update }(x_i, \theta; \mathcal{H}) := \theta - \eta \cdot \frac{1}{n_i} \sum_{j=1}^{n_i} \nabla \ell(\theta, x_{i,j}).$$

Alternatively, a gradient update with step size $\alpha_i \in \mathcal{H}$ can be performed such that

$$\text{Update }(x_i, \theta; \mathcal{H}) := \theta - \alpha_i \cdot \frac{1}{m} \sum_{j=1}^{m} \nabla \ell(\theta, x_{i,j}).$$

Alternatively, stochastic proximal-point-type updates can be applied, such that

$$\text{Update }(x_i, \theta; \mathcal{H}) := \underset{\theta}{\text{argmin}} \left\{ \frac{1}{m} \sum_{j=1}^{m} \ell(\theta, x_{i,j}) + \frac{1}{2\alpha_i} \| \theta - \theta_0 \|_2^2 \right\}.$$

With respect to the operations to generate individualized model updates (block **403**), privatize the individual model updates (block **404**), and transmit the privatized model updates (block **405**), a privatized version of model differences $\Delta_i = \theta_i - \theta$ are generated for transmission to the server using a separated mechanism, rather than submitting Δ_i directly to the server. Where Z_1 is an unbiased (private) estimate of $\Delta_i / \|\Delta_i\|$ and Z_2 is an unbiased estimate of $\|\Delta_i\|$, a value $\Delta_i = Z_1 Z_2$ is transmitted to the server.

In one embodiment a privatized difference $\hat{\Delta}_i$ is transmitted via a separated differential privacy algorithm. In one embodiment, privatized difference $\hat{\Delta}_i$ is generated by a combination of a unit vector privatization technique, PrivUnit$_2$ and a magnitude privatization technique AbsMagnDP, where the pair is separated differentially private, such that

$$\hat{\Delta}_i \leftarrow PrivUnit_2\left(\frac{\Delta_i}{\|\Delta_i\|_2}, \gamma, \varepsilon'\right)\cdot \mathrm{Abs}MagnDP(\|\Delta_i\|_2, \nu).$$

In one embodiment, privatized unit vectors can also be generated via a mechanism PrivUnit$_\infty$, while magnitudes can be privatized via mechanisms PrivMagn or RelMagnDP, which are described in further detail in FIG. **6**A-**6**C.

To generate an aggregate model update on the learning server (block **406**), once the server has all the privatized updates from each device in the selected batch $\mathcal{B}$, i. e. $\{\hat{\Delta}_i \in \mathcal{B}\}$, the server then aggregates the privatized updates to form a single update to the server model. The server can clip each gradient update with function Clip for radius S>0, where

$$\mathrm{Clip}(\hat{\Delta}_i; S) = \hat{\Delta}_i \cdot \min\{S/\|\hat{\Delta}_i\|_2, 1\}.$$

The aggregated update then becomes the following for N users, where each device's update is weighted equally

$$\hat{\Delta} \leftarrow \frac{1}{qN}\sum_{i\in\mathcal{B}} Clip(\hat{\Delta}_i; S).$$

Alternatively, given a collection of privatized updates $\{\hat{\Delta}_i\}_{i\in\mathcal{B}}$, aggregation can be performed by projecting each update onto an ℓ_2-ball of radius S>0. Letting $\pi_S(v)=v\min\{S/\|v\|_2, 1\}$ denote this projection, the aggregate update can be defined as

$$\hat{\Delta} \leftarrow \frac{1}{qN}\sum_{i\in\mathcal{B}} \pi_S(\Delta_i).$$

For online stochastic gradient settings, where $\Delta_i = \alpha\nabla\ell(\theta, x_i)$ for a stepsize α that decreases to zero as the iterative procedure continues, we eventually have (with probability 1) that $\|\nabla\ell(\theta, x_i)\|_2 \le r/\alpha$ for any r>0 as $\alpha\downarrow 0$. The truncation to a radius S allows central privacy protections.

Local privatization with separated differential privacy provides strong safeguards against reconstruction breaches from adversaries with some prior knowledge. Aggregate model privatization (block **407**) is performed to prevent any one user from substantially impacting the overall server model with their local data, to prevent overfitting, and to enable privacy for server data. Aggregate model privatization is performed by incorporating central differential privacy into the separated differential privacy model used for model updates.

In one embodiment, the aggregate update

$$\hat{\Delta} \leftarrow \frac{1}{qN}\Sigma_{i\in\mathcal{B}}\pi_S(\Delta_i)$$

described above has ℓ_2-sensitivity at most S/(qN) (modifying a single update Δ_i can cause $\hat{\Delta}$ to change by at most S/(qN) in ℓ_2-distance). Consequently, addition of appropriate Gaussian noise enables a guarantee of (ε,δ)-approximate

differential privacy. Assuming computation of a total of T global updates, and where $\varepsilon>0$ and $\delta\in(0,1)$ are the desired approximate privacy parameters. Letting

$$Z \sim N(0, S^2\sigma^2 I_d),\ \sigma^2 := \frac{4q^2 T\log\frac{1}{\delta}}{\varepsilon^2},\ \theta \leftarrow \theta + Z. \quad (11)$$

Then each update to θ is (ε,δ)-differentially private.

Privacy definitions for central differential privacy and separate differential privacy as used by embodiments described herein are provided below.

It can be said that two datasets D, D'$\in\mathcal{D}$ are neighboring if D is the same as D' except at most one datum is added to or removed from D'. In the central setting, an algorithm M: $\mathcal{D}\rightarrow\mathcal{Y}$ is (ε,δ)-differentially private if for all neighboring datasets D, D'$\in\mathcal{D}$ and for all outcome sets $S\subset\gamma$ we have

$$\mathbb{P}[M(D)\in S] \le e^{\varepsilon}\,\mathbb{P}[M(D')\in S] + \delta$$

The privacy model used for private federated learning as described herein considers settings in which a random variable W over domain $\mathcal{W}$ is present, with two corresponding downstream variables U from domain $\mathcal{U}$ and R from domain $\mathcal{R}$, governed by the Markovian graphical structure U←W→R. The variable W may correspond to the gradient $\nabla\ell(\theta;X)$ of the loss at the current parameter θ with data X (or otherwise a particular model update), while $U=W/\|W\|_2$ is its normalized value and $R=\|W\|_2$ is its radius or norm.

FIG. **5**A-**5**B illustrates techniques for privatizing model updates, according to an embodiment. FIG. **5**A illustrates a Markovian graphical structure **500** between data X and privatized pair (Z_1,Z_2). Considering a setting in which a user or study participant has data X (**501**) which is intended to remain private. Data X is transformed into a vector W (**502**), which may simply be an identity transformation, but can also be a gradient of the loss ℓ on the datum X or other derived statistic. Vector W can be represented by unit direction U(**504**), where $U=W/\|W\|_2$ and magnitude R(**503**), where $R=\|W\|_2$. Unit direction U(**504**) and magnitude R(**503**) can be privatized into privatized unit vector $\mathcal{Z}_1$(**506**) and privatized radius or magnitude $\mathcal{Z}_2$(**505**). In light of this graphical structure, embodiments described herein present several mechanisms $M_1: \mathcal{U}\rightarrow\mathcal{Z}_1$ and $M_2: \mathcal{R}\rightarrow\mathcal{Z}_2$ that map pair (U,R) into privatized pair (Z_1, Z_2).

The mechanism $M: \mathcal{U}\times\mathcal{R}\rightarrow\mathcal{Z}_1\times\mathcal{Z}_2$ can be written as the pair $M(U,R)=(M_1(U), M_2(R))=(Z_1,Z_2)$. The pair (Z_1,Z_2) does not give substantial information about the input, which allows separated differential privacy to protect against reconstruction breaches. The separated differential privacy protections are specifically tailored to protect against certain curious onlooker adversaries, which can be represented by prior distributions over the triple (U, W, R).

To define separated differential privacy, consider the triples (U, W, R) with the Markovian graphical structure described above. A pair of mechanisms M_1, M_2 mapping from $\mathcal{U}\times$R to $\mathcal{Z}_1\times\mathcal{Z}_2$ is (ε,ρ)-separated differentially private if M_1 is ε-differentially and M_2 is ρ-differentially private.

(i) The mechanism $M_1: \mathcal{U}\rightarrow\mathcal{Z}_1$ is ε-differentially private, i.e. for any u,u'$\in\mathcal{U}$ and outcome set $S\subset\mathcal{Z}_1$,

$$\frac{\mathbb{P}(M_1(u)\in S)}{\mathbb{P}(M_1(u')\in S)} \le e^{\varepsilon}.$$

(ii) The mechanism $M_2: \mathcal{U} \rightarrow \mathbb{Z}_2$ is ρ-differentially private, i.e. for any r, r'∈R and outcome set $S \subset \mathbb{Z}_2$,

$$\frac{\mathbb{P}(M_2(r) \in S)}{\mathbb{P}(M_2(r) \in S)} \leq e^{\rho}$$

The algorithms above enable separated differential privacy and can be shown to be sufficient to guarantee strong reconstruction protections for high-dimensional data for a large range of ε, ρ parameters when the adversary knows relatively little a priori about the actual input.

FIG. **5**B illustrates a method **510** of privatizing model updates, according to an embodiment. Method **510** can be performed on a client device (e.g., client device **310**) of the set of client devices selected to send a model update to a model update server (e.g., server **130**). In one embodiment, method **510** includes an operation (block **511**) to obtain a weight vector that represents a difference between a previous and recently trained model. This difference represents the model update that is to be transmitted to the learning server to update the current server model. Method **510** additionally includes an operation (block **512**) to decompose the weight vector into a unit vector (e.g., unit direction $U=W/\|W\|_2$) and a magnitude (e.g., radius $R=\|W\|_2$). Method **500** additionally includes an operation (block **513**) to privatize the unit vector. The unit vector can be privatized via mapping mechanism $M_1: \mathcal{U} \rightarrow \mathbb{Z}_1$ described above. In one embodiment the unit vector is privatized using a technique (PrivUnit_2) to minimize the ℓ_2-norm of the privatized vector. Other techniques can also be used. In one embodiment the unit vector can be privatized based on ℓ_∞-unit vectors on the unit cube, i.e., $u \in \mathbb{H}^d := \{u \in \mathbb{R}^d : \|u\|_\infty = 1\}$ (e.g., PrivUnit_∞).

Method **510** additionally includes an operation (block **514**) to separately privatize the magnitude. The magnitude can be privatized via mapping mechanism $M_2: \mathcal{R} \rightarrow \mathbb{Z}_2$ described above. The mapping mechanism can be based on relative noise (PrivMagn) and will be privatized based on assumptions made about the availability of the data available to the attacker. The mapping mechanism can also be a differentially private mechanism, which can be an absolute error-based mechanism (AbsMagnDP) or a relative error-based mechanism (RelMagnDP).

Method **510** additionally includes an operation (block **515**) to transmit the privatized unit vector and magnitude to the learning server as the model update. For example, where the model update is represented by model difference $\hat{\Delta}_i$, the model difference is transmitted as differentially private pair PrivUnit_2 and PrivMagn, where the pair is separated differentially private, such that

$$\hat{\Delta}_i \leftarrow \mathit{PrivUnit}_2\left(\frac{\Delta_i}{\|\Delta_i\|_2}, \gamma, \varepsilon'\right) \cdot \mathrm{Abs}\mathit{MagnDP}(\|\Delta_i\|_2, \nu).$$

Alternatively, the unit vector for the model difference can be transmitted using mechanism PrivUnit_∞ which is based on ℓ_∞-unit vectors. The magnitude can also be privatized using a relative noise-based mechanism RelMagnDP or a relative error-based mechanism PrivMagn under additional assumptions about the adversary.

FIG. **6**A-**6**C illustrate algorithms to generate a privatized unit vector and privatized magnitude, according to embodiments. FIG. **6**A illustrates methods **601**, **602**, **603** to generate a privatized unit vector and privatized magnitude, according to embodiments. In one embodiment, method **601** can be used to generate privatized unit vector PrivUnit_2. Specifically, method **601** takes as input unit vector $u \in \mathbb{S}^{d-1}$ and parameter $\gamma \in [0,1]$ and returns privatized vector Z, which has the property that $\mathbb{E}[Z|u]=u$. The mechanism of method **601** then draws a vector V uniformly from a cap $\{v \in \mathbb{S}^{d-1} | \langle v, u \rangle > \gamma\}$ with probability

$$\frac{e^{\varepsilon'}}{1+e^{\varepsilon'}}$$

or otherwise uniformly from its complement $\{v \in \mathbb{S}^{d-1} | \langle v, u \rangle < \gamma\}$. The mechanism of method **601** then sets a and z values such that

$$\alpha = \frac{d-1}{2}, \tau = \frac{1+\gamma}{2}$$

Method **601** then makes use of the incomplete beta function

$$B(x; \alpha, \beta) := \int_0^x t^{\alpha-1}(1-t)^{\beta-1}\,dt$$

$$\text{where } B(\alpha, \beta) := B(1; \alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}.$$

to compute a value for m, such that

$$m = \frac{(1-\gamma^2)^\alpha}{2^{d-1}(d-1)(1+e^{\varepsilon'})}\left[\frac{1}{B(\alpha,\alpha) - B(\tau,\alpha,\alpha)} - \frac{1}{B(\tau,\alpha,\alpha)}\right]$$

Method **601** then sets

$$Z = \frac{1}{m} \cdot V$$

and transmits private value Z.

Method **602** is an alternative to the PrivUnit_2 mechanism, in which a PrivUnit_∞ is a mechanism based on ℓ_∞-unit vectors on the unit cube, i.e $u \in \mathbb{H}^d := \{u \in \mathbb{R}^d = \|u\|_\infty = 1\}$ and returns ε-differentially private vector Z, which has the property that $\mathbb{E}[Z|u]=u$ for all $u \in \mathbb{H}^d$, where the size of Z (its ℓ_∞-norm $\|Z\|_\infty$) is as small as possible.

As illustrated, given $u \in \mathbb{H}^d$, $\kappa \in \{0, \ldots, d-1\}$, ε'≥0, method **602** includes to round each coordinate of $u=(u_1, \ldots, u_d)$ to a corner of $\mathbb{H}^d$. Then, for j∈[d] do

$$\hat{U}_j = \begin{cases} 1 & w.p.\ \frac{1+u_j}{2} \\ -1 & \text{else} \end{cases}$$

Method **602** additionally includes an operation to draw random vector V according to the following distribution,

$$V = \begin{cases} \text{uniform on } \left\{v \in \{-1,+1\}^d \,\middle|\, \langle v, \hat{U} \rangle > \kappa \right\} & \text{with probability } \frac{e^{\varepsilon'}}{e^{\varepsilon}+1} \\ \text{uniform on } \left\{v \in \{-1,+1\}^d \,\middle|\, \langle v, \hat{U} \rangle \leq \kappa \right\} & \text{otherwise.} \end{cases}$$

An additional operation can be performed to set

$$\tau = \frac{\left\lceil \frac{d+\kappa+1}{2} \right\rceil}{d}$$

and debias the vector

$$m = \frac{1}{e^{\varepsilon'}+1} \cdot \left(\frac{e^{\varepsilon'} \binom{d-1}{d\tau-1}}{\sum_{\ell=\tau \cdot d}^{d} \binom{d}{\ell}} - \frac{\binom{d-1}{d\tau-1}}{\sum_{\ell=0}^{d\tau-1} \binom{d}{\ell}} \right)$$

Method **602** additionally includes an operation to set

$$Z = \frac{1}{m} \cdot V$$

and transmit Z.

An efficient approach to implement the sampling of method **602** is to first sample a Bernoulli B with success probability

$$\frac{e^{\varepsilon'}}{e^{\varepsilon}+1}.$$

If B=0, then use rejection sampling to generate a uniform random vector V~Uni($\{-1,1\}^d$) and only accept if <V,Û>≤K. Otherwise, if B=1 then sample a conditional Binomial random variable B' with the following CDF and use the inverse transform sampling technique,

$$F(t) := \mathbb{P}[B' \leq t] = \frac{\sum_{\ell=d\tau}^{t} \binom{d}{\ell}}{\sum_{\ell'=d\tau}^{d} \binom{d}{\ell'}}.$$

The random variable B' indicates the number of coordinates of Û that the random vector V needs to match. Uniform sampling of B' coordinates of Û is performed and corresponding coordinates of V are set to be the same. The remaining coordinates of V are then set to be the flipped value of the corresponding coordinates of Û.

Method **603** generates a privatized magnitude (PrivMagn). Method **603** takes as input r magnitude and v>0 and returns a privatized magnitude r·X, where r=$\|W\|_2$ of a vector w∈$\mathbb{R}^d$. Method **602** includes to sample Y~Uni[−v,v] and set

$$X = 2v \cdot \frac{\exp(Y)}{\exp(v) - \exp(-v)}.$$

Privatized magnitude r·X can then be transmitted to the server.

FIG. **6**B illustrates methods **604**, **605** to generate privatized magnitudes for transmission to a server. Methods **604** and **605** present two mechanisms for the e-differentially-private release of a single variable (value) r∈[0,r_{max}], where r_{max} is some a priori upper bound of r. Method **604** enables mechanism AbsMagnDP, which achieves order optimal scaling for the mean-squared error $\mathbb{E}$ [$(Z-r)^2$|r], which is

$$r_{max}^2 e^{-2\varepsilon/3}$$

for ε≥1. Method **605** enables mechanism RelMagnDP, which achieves a truncated relative error guarantee, which for a fixed threshold α_0∈[$e^{-\varepsilon/2}$,1] is

$$\mathbb{E}\left[(Z-r)^2 \,\middle|\, r\right] = O\left(\max\{r, r_{max}\alpha_0\}^2 \left(\alpha_0^2 e^{\varepsilon}\right)^{-2/3}\right).$$

For Method **604**, a value k∈ℕ is fixed. Then r is randomly rounded to an index value J taking values in {0, 1, 2, . . . , k} with the property that

$$\mathbb{E}\left[\frac{r_{max} J}{k} \,\middle|\, r\right] = r \text{ and } \frac{kr}{r_{max}} \leq J \leq \frac{kr}{r_{max}}.$$

Next, a random response is employed over k outcomes to obtain Ĵ, which is then debiased to obtain Z, which is an estimator for r.

Method **605** provides an alternate differential privacy mechanism that enables a relative error guarantee. The mechanism provided by method **605** breaks the range r∈[0, r_{max}] into intervals of increasing length based on a fixed accuracy α>0, k∈ℕ, and v>1. Intervals can be constructed such that

$$E_0=[0,v\alpha], E_i=[v^i\alpha, v^{i+1}\alpha] \text{ for } i=1, \ldots, k-1.$$

Once it is determined which interval to which r belongs, r can be assigned to an end point of the interval at random to obtain an unbiased estimator. A randomized response is then used to obtain Ĵ, which is then debiased to obtain Z, which is an estimator for r.

FIG. **6**C illustrates method **606**, which enables an optimization that provides for the efficient sampling of unit vectors in PrivUnit$_2$. Specifically, method **606** provides an efficient mechanism to perform the sampling of Z in **601**.

Method **606**, given u∈$\mathbb{S}^{d-1}$ and γ∈[0,1], specifies to sample

$$Y = Bern\left(\frac{e^{\varepsilon'}}{e^{\varepsilon}+1}\right).$$

If Y=1, then sample B'=2B−1 where

$$B \sim \text{Beta}\left(\frac{d-1}{2}, \frac{d-1}{2}\right)$$

conditioned on

$$B \geq \frac{\gamma+1}{2};$$

Set $\hat{U} \leftarrow B' \cdot u$; Draw $U \sim \mathrm{Uni}(\mathbb{S}^{d-1})$; Set

$$V \leftarrow \sqrt{1 - B'^2} \cdot \frac{(I - uu^T)U}{\left\|(I_d - uu^T) \cdot U\right\|_2};$$

and Set $V \leftarrow \hat{U} + V$. Otherwise, perform rejection sampling, i.e. Bool←True; while Bool do: Draw $U \sim \mathrm{Uni}(\mathbb{S}^{d-1})$. If $\langle U, u \rangle < \gamma$, then V←U; Bool=False. Value V can then be provided for use in determining Z as in method **602**, where

$$Z = \frac{1}{m} \cdot V.$$

FIG. **7** illustrates compute architecture **700** on a client device that can be used to enable on-device training using machine learning algorithms, according to embodiments described herein. In one embodiment, compute architecture **700** includes a client machine learning framework **702** that can be configured to leverage a processing system **720** on a client device. The client machine learning framework **702** includes a vision/image framework **704**, a language processing framework **706**, and one or more other frameworks **708**, which each can reference primitives provided by a core machine learning framework **710**. The core machine learning framework **710** can access resources provided via a CPU acceleration layer **712**, neural network processor acceleration layer **713** and a GPU acceleration layer **714**. The CPU acceleration layer **712**, neural network processor acceleration layer **713**, and the GPU acceleration layer **714** each facilitate access to a processing system **720** on the various client devices described herein.

The processing system includes an application processor **722**, a neural network processor **723**, and a graphics processor **724**, each of which can be used to accelerate operations of the core machine learning framework **710** and the various higher-level frameworks that operate via primitives provided via the core machine learning framework. The application processor **722** and graphics processor **724** include hardware that can be used to perform general-purpose processing and graphics specific processing for the core machine learning framework **710**. The neural network processor **723** includes hardware that is tuned specifically to accelerate processing operations for artificial neural networks. The neural network processor **723** can increase speed at which neural network operations are performed but is not required to enable the operation of the client machine learning framework **702**. For example, training can also be performed using the application processor **722** and/or the graphics processor **724**.

In one embodiment, the various frameworks and hardware resources of the compute architecture **700** can be used for inferencing operations as well as training operations. For example, a client device can use the compute architecture **700** to perform supervised learning via a machine learning model as described herein, such as but not limited to a CNN, RNN, or LSTM model. The client device can then use the trained machine learning model to perform classification operations for one or a variety of predictive models including but not limited to a natural language processing model, a predictive text model, an application suggestion model, and application activity suggestion model, a voice classification model, and an image classification model.

FIG. **8** is a block diagram of a device architecture **800** for a mobile or embedded device, according to an embodiment. The device architecture **800** includes a memory interface **802**, a processing system **804** including one or more data processors, image processors and/or graphics processing units, and a peripherals interface **806**. The various components can be coupled by one or more communication buses or signal lines. The various components can be separate logical components or devices or can be integrated in one or more integrated circuits, such as in a system on a chip integrated circuit.

The memory interface **802** can be coupled to memory **850**, which can include high-speed random-access memory such as static random-access memory (SRAM) or dynamic random-access memory (DRAM) and/or non-volatile memory, such as but not limited to flash memory (e.g., NAND flash, NOR flash, etc.).

Sensors, devices, and subsystems can be coupled to the peripherals interface **806** to facilitate multiple functionalities. For example, a motion sensor **810**, a light sensor **812**, and a proximity sensor **814** can be coupled to the peripherals interface **806** to facilitate the mobile device functionality. One or more biometric sensor(s) **815** may also be present, such as a fingerprint scanner for fingerprint recognition or an image sensor for facial recognition. Other sensors **816** can also be connected to the peripherals interface **806**, such as a positioning system (e.g., GPS receiver), a temperature sensor, or other sensing device, to facilitate related functionalities. A camera subsystem **820** and an optical sensor **822**, e.g., a charged coupled device (CCD) or a complementary metal-oxide semiconductor (CMOS) optical sensor, can be utilized to facilitate camera functions, such as recording photographs and video clips.

Communication functions can be facilitated through one or more wireless communication subsystems **824**, which can include radio frequency receivers and transmitters and/or optical (e.g., infrared) receivers and transmitters. The specific design and implementation of the wireless communication subsystems **824** can depend on the communication network(s) over which a mobile device is intended to operate. For example, a mobile device including the illustrated device architecture **800** can include wireless communication subsystems **824** designed to operate over a GSM network, a CDMA network, an LTE network, a Wi-Fi network, a Bluetooth network, or any other wireless network. In particular, the wireless communication subsystems **824** can provide a communications mechanism over which a media playback application can retrieve resources from a remote media server or scheduled events from a remote calendar or event server.

An audio subsystem **826** can be coupled to a speaker **828** and a microphone **830** to facilitate voice-enabled functions, such as voice recognition, voice replication, digital recording, and telephony functions. In smart media devices described herein, the audio subsystem **826** can be a high-quality audio system including support for virtual surround sound.

The I/O subsystem **840** can include a touch screen controller **842** and/or other input controller(s) **845**. For computing devices including a display device, the touch screen controller **842** can be coupled to a touch sensitive display system **846** (e.g., touch-screen). The touch sensitive display system **846** and touch screen controller **842** can, for example, detect contact and movement and/or pressure using any of a plurality of touch and pressure sensing technologies, including but not limited to capacitive, resistive, infrared, and surface acoustic wave technologies, as well as other proximity sensor arrays or other elements for determining one or more points of contact with a touch sensitive display system **846**. Display output for the touch sensitive display system **846** can be generated by a display controller **843**. In one embodiment, the display controller **843** can provide frame data to the touch sensitive display system **846** at a variable frame rate.

In one embodiment, a sensor controller **844** is included to monitor, control, and/or processes data received from one or more of the motion sensor **810**, light sensor **812**, proximity sensor **814**, or other sensors **816**. The sensor controller **844** can include logic to interpret sensor data to determine the occurrence of one of more motion events or activities by analysis of the sensor data from the sensors.

In one embodiment, the I/O subsystem **840** includes other input controller(s) **845** that can be coupled to other input/control devices **848**, such as one or more buttons, rocker switches, thumb-wheel, infrared port, USB port, and/or a pointer device such as a stylus, or control devices such as an up/down button for volume control of the speaker **828** and/or the microphone **830**.

In one embodiment, the memory **850** coupled to the memory interface **802** can store instructions for an operating system **852**, including portable operating system interface (POSIX) compliant and non-compliant operating system or an embedded operating system. The operating system **852** may include instructions for handling basic system services and for performing hardware dependent tasks. In some implementations, the operating system **852** can be a kernel.

The memory **850** can also store communication instructions **854** to facilitate communicating with one or more additional devices, one or more computers and/or one or more servers, for example, to retrieve web resources from remote web servers. The memory **850** can also include user interface instructions **856**, including graphical user interface instructions to facilitate graphic user interface processing.

Additionally, the memory **850** can store sensor processing instructions **858** to facilitate sensor-related processing and functions; telephony instructions **860** to facilitate telephone-related processes and functions; messaging instructions **862** to facilitate electronic-messaging related processes and functions; web browser instructions **864** to facilitate web browsing-related processes and functions; media processing instructions **866** to facilitate media processing-related processes and functions; location services instructions including GPS and/or navigation instructions **868** and Wi-Fi based location instructions to facilitate location based functionality; camera instructions **870** to facilitate camera-related processes and functions; and/or other software instructions **872** to facilitate other processes and functions, e.g., security processes and functions, and processes and functions related to the systems. The memory **850** may also store other software instructions such as web video instructions to facilitate web video-related processes and functions; and/or web shopping instructions to facilitate web shopping-related processes and functions. In some implementations, the media processing instructions **866** are divided into audio processing instructions and video processing instructions to facilitate audio processing-related processes and functions and video processing-related processes and functions, respectively. A mobile equipment identifier, such as an International Mobile Equipment Identity (IMEI) **874** or a similar hardware identifier can also be stored in memory **850**.

Each of the above identified instructions and applications can correspond to a set of instructions for performing one or more functions described above. These instructions need not be implemented as separate software programs, procedures, or modules. The memory **850** can include additional instructions or fewer instructions. Furthermore, various functions may be implemented in hardware and/or in software, including in one or more signal processing and/or application specific integrated circuits.

FIG. **9** is a block diagram of a computing system **900**, according to an embodiment. The illustrated computing system **900** is intended to represent a range of computing systems (either wired or wireless) including, for example, desktop computer systems, laptop computer systems, tablet computer systems, cellular telephones, personal digital assistants (PDAs) including cellular-enabled PDAs, set top boxes, entertainment systems or other consumer electronic devices, smart appliance devices, or one or more implementations of a smart media playback device. Alternative computing systems may include more, fewer and/or different components. The computing system **900** can be used to provide the computing device and/or a server device to which the computing device may connect.

The computing system **900** includes bus **935** or other communication device to communicate information, and processor(s) **910** coupled to bus **935** that may process information. While the computing system **900** is illustrated with a single processor, the computing system **900** may include multiple processors and/or co-processors. The computing system **900** further may include memory **920**, such as random-access memory (RAM) or other dynamic storage device coupled to the bus **935**. The memory **920** may store information and instructions that may be executed by processor(s) **910**. The memory **920** may also be used to store temporary variables or other intermediate information during execution of instructions by the processor(s) **910**.

The computing system **900** may also include read only memory (ROM) **930** and/or another data storage device **940** coupled to the bus **935** that may store information and instructions for the processor(s) **910**. The data storage device **940** can be or include a variety of storage devices, such as a flash memory device, a magnetic disk, or an optical disc and may be coupled to computing system **900** via the bus **935** or via a remote peripheral interface.

The computing system **900** may also be coupled, via the bus **935**, to a display device **950** to display information to a user. The computing system **900** can also include an alphanumeric input device **960**, including alphanumeric and other keys, which may be coupled to bus **935** to communicate information and command selections to processor(s) **910**. Another type of user input device includes a cursor control **970** device, such as a touchpad, a mouse, a trackball, or cursor direction keys to communicate direction information and command selections to processor(s) **910** and to control cursor movement on the display device **950**. The computing system **900** may also receive user input from a remote device that is communicatively coupled via one or more network interface(s) **980**.

The computing system **900** further may include one or more network interface(s) **980** to provide access to a network, such as a local area network. The network interface(s) **980** may include, for example, a wireless network interface having antenna **985**, which may represent one or more antenna(e). The computing system **900** can include multiple wireless network interfaces such as a combination of Wi-Fi, Bluetooth®, near field communication (NFC), and/or cellular telephony interfaces. The network interface(s) **980** may also include, for example, a wired network interface to communicate with remote devices via network cable **987**, which may be, for example, an Ethernet cable, a coaxial cable, a fiber optic cable, a serial cable, or a parallel cable.

In one embodiment, the network interface(s) **980** may provide access to a local area network, for example, by conforming to IEEE 802.11 standards, and/or the wireless network interface may provide access to a personal area network, for example, by conforming to Bluetooth standards. Other wireless network interfaces and/or protocols can also be supported. In addition to, or instead of, communication via wireless LAN standards, network interface(s) **980** may provide wireless communications using, for example, Time Division, Multiple Access (TDMA) protocols, Global System for Mobile Communications (GSM) protocols, Code Division, Multiple Access (CDMA) protocols, Long Term Evolution (LTE) protocols, and/or any other type of wireless communications protocol.

The computing system **900** can further include one or more energy sources **905** and one or more energy measurement systems **945**. Energy sources **905** can include an AC/DC adapter coupled to an external power source, one or more batteries, one or more charge storage devices, a USB charger, or other energy source. Energy measurement systems include at least one voltage or amperage measuring device that can measure energy consumed by the computing system **900** during a predetermined period of time. Additionally, one or more energy measurement systems can be included that measure, e.g., energy consumed by a display device, cooling subsystem, Wi-Fi subsystem, or other frequently used or high-energy consumption subsystem.

In some embodiments, the hash functions described herein can utilize specialized hardware circuitry (or firmware) of the system (client device or server). For example, the function can be a hardware-accelerated function. In addition, in some embodiments, the system can use a function that is part of a specialized instruction set. For example, the hardware can use an instruction set which may be an extension to an instruction set architecture for a particular type of microprocessors. Accordingly, in an embodiment, the system can provide a hardware-accelerated mechanism for performing cryptographic operations to improve the speed of performing the functions described herein using these instruction sets.

In addition, the hardware-accelerated engines/functions are contemplated to include any implementations in hardware, firmware, or combination thereof, including various configurations which can include hardware/firmware integrated into the SoC as a separate processor, or included as special purpose CPU (or core), or integrated in a coprocessor on the circuit board, or contained on a chip of an extension circuit board, etc.

It should be noted that the term “approximately” or “substantially” may be used herein and may be interpreted as “as nearly as practicable,” “within technical limitations,” and the like. In addition, the use of the term “or” indicates an inclusive or (e.g. and/or) unless otherwise specified.

As described above, one aspect of the present technology is the gathering and use of data available from various specific and legitimate sources to enable crowdsource learning of sequential data. The present disclosure contemplates that in some instances, this gathered data may include personal information data that uniquely identifies or can be used to identify a specific person. Such personal information data can include demographic data, location-based data, online identifiers, telephone numbers, email addresses, social media IDs, home addresses, data or records relating to a user’s health or level of fitness (e.g., vital signs measurements, medication information, exercise information), date of birth, or any other identifying or personal information.

The present disclosure recognizes that the use of such personal information data, in the present technology, can be used to the benefit of users. For example, the personal information data can be used to learn new words, improve keyboard layouts, improve autocorrect engines for keyboards, and to enable an electronic device to better anticipate the needs of a user. Further, other uses for personal information data that benefit the user are also contemplated by the present disclosure. For instance, health and fitness data may be used, in accordance with the user’s preferences, to provide insights into their general wellness, or may be used as positive feedback to individuals using technology to pursue wellness goals.

The present disclosure contemplates that those entities responsible for the collection, analysis, disclosure, transfer, storage, or other use of such personal information data will comply with well-established privacy policies and/or privacy practices. In particular, such entities would be expected to implement and consistently apply privacy practices that are generally recognized as meeting or exceeding industry or governmental requirements for maintaining the privacy of users. Such information regarding the use of personal data should be prominently and easily accessible by users and should be updated as the collection and/or use of data changes. Personal information from users should be collected for legitimate uses only. Further, such collection/sharing should occur only after receiving the consent of the users or other legitimate basis specified in applicable law. Additionally, such entities should consider taking any needed steps for safeguarding and securing access to such personal information data and ensuring that others with access to the personal information data adhere to their privacy policies and procedures. Further, such entities can subject themselves to evaluation by third parties to certify their adherence to widely accepted privacy policies and practices. In addition, policies and practices should be adapted for the particular types of personal information data being collected and/or accessed and adapted to applicable laws and standards, including jurisdiction-specific considerations which may serve to impose a higher standard. For instance, in the US, collection of or access to certain health data may be governed by federal and/or state laws, such as the Health Insurance Portability and Accountability Act (HIPAA); whereas health data in other countries may be subject to other regulations and policies and should be handled accordingly.

Despite the foregoing, the present disclosure also contemplates embodiments in which users selectively block the use of, or access to, personal information data. That is, the present disclosure contemplates that hardware and/or software elements can be provided to prevent or block access to such personal information data. For example, the present technology can be configured to allow users to select to “opt in” or “opt out” of participation in the collection of personal information data during registration for services or anytime thereafter. In addition to providing “opt in” and “opt out” options, the present disclosure contemplates providing notifications relating to the access or use of personal information. For instance, a user may be notified upon downloading an app that their personal information data will be accessed and then reminded again just before personal information data is accessed by the app.

Moreover, it is the intent of the present disclosure that personal information data should be managed and handled in a way to minimize risks of unintentional or unauthorized access or use. Risk can be minimized by limiting the collection of data and deleting data once it is no longer needed. In addition, and when applicable, including in certain health related applications, data de-identification can be used to protect a user's privacy. De-identification may be facilitated, when appropriate, by removing identifiers, controlling the amount or specificity of data stored (e.g., collecting location data at city level rather than at an address level), controlling how data is stored (e.g., aggregating data across users), and/or other methods such as differential privacy.

Therefore, although the present disclosure broadly covers use of personal information data to implement one or more various disclosed embodiments, the present disclosure also contemplates that the various embodiments can also be implemented without the need for accessing such personal information data. That is, the various embodiments of the present technology are not rendered inoperable due to the lack of all or a portion of such personal information data. For example, crowdsourcing of sequences can be performed over a large number of users and is based on aggregated, non-personal information data. A large number of individual users can opt out of sending data to the sequence learning server and overall trends can still be detected.

In the foregoing description, example embodiments of a private federated learning system have been described. It will be evident that various modifications can be made thereto without departing from the broader spirit and scope of the disclosure. The specification and drawings are, accordingly, to be regarded in an illustrative sense rather than a restrictive sense. The specifics in the descriptions and examples provided may be used anywhere in one or more embodiments. The various features of the different embodiments or examples may be variously combined with some features included and others excluded to suit a variety of different applications. Examples may include subject matter such as a method, means for performing acts of the method, at least one machine-readable medium including instructions that, when performed by a machine cause the machine to perform acts of the method, or of an apparatus or system according to embodiments and examples described herein. Additionally, various components described herein can be a means for performing the operations or functions described herein.

One embodiment described herein provides for a non-transitory machine-readable medium storing instructions to cause one or more processors of a data processing system to perform operations comprising receiving a machine learning model from a server at a client device, training the machine learning model using local data at the client device, generating an update for the machine learning model, the update including a weight vector that represents a difference between the received machine learning model and the trained machine learning model, privatizing the update for the machine learning model, and transmitting the privatized update for the machine learning model to the server.

One embodiment described herein provides for a data processing system comprising a memory to store instructions and one or more processors to execute the instructions. The instructions cause the one or more processors to receive a machine learning model from a server at a client device, train the machine learning model using local data at the client device to generate a trained machine learning model, generate an update for the machine learning model, the update including a weight vector that represents a difference between the machine learning model and the trained machine learning model, privatize the update for the machine learning model, and transmit the privatized update for the machine learning model to the server.

One embodiment described herein provides for a method comprising receiving a machine learning model from a server at a client device, training the machine learning model using local data at the client device to generate a trained machine learning model, generating an update for the machine learning model, the update including a weight vector that represents a difference between the machine learning model and the trained machine learning model, privatizing the update for the machine learning model, and transmitting the privatized update for the machine learning model to the server.

In the embodiments described herein, local model updates generated by user devices are privatized using mechanisms that can be shown to be sufficient to guarantee strong reconstruction protections for high-dimensional data for a large range of $\in$, ρ parameters when the adversary knows relatively little a priori about the actual input. The various privacy mechanisms described herein can be employed without reducing the utility of the data for learning operations.

In some embodiments, separated differential privacy mechanisms are employed. The separated differential privacy mechanisms can decompose a model update into a unit vector and magnitude, then separately privatize the unit vector and magnitude for each update to the machine learning model before the update is transmitted by the user device. In one embodiment the magnitude is privatized with absolute error. In one embodiment the magnitude is privatized with relative error. In one embodiment the unit vector is privatized based on ℓ_2-unit vectors on the unit cube. In one embodiment, the unit vector is privatized based on ℓ_∞-unit vectors on the unit cube.

The machine learning models described herein can be used in a variety of applications, including natural language processing, mage classification, or voice classification. After a model is updated using aggregated model updates, the updated model, or the simply the updates to the model, can be re-transmitted to the client devices for further training and updates.

Other features of the present embodiments will be apparent from the accompanying drawings and from the detailed description above. Accordingly, the true scope of the embodiments will become apparent to the skilled practitioner upon a study of the drawings, specification, and following claims.

What is claimed is:

1. A non-transitory machine-readable medium storing instructions to cause one or more processors of a data processing system to perform operations comprising:
- receiving a machine learning model from a server at a client device;
- training the machine learning model using local data at the client device to generate a trained machine learning model;
- determining a weight vector that is a difference between first weights of the machine learning model and second weights of the trained machine learning model;
- generating an update for the machine learning model, the update including the weight vector;
- privatizing the update for the machine learning model by separately privatizing a magnitude and a unit vector of the update; and
- transmitting the privatized update for the machine learning model to the server.

2. The non-transitory machine-readable medium as in claim **1**, wherein privatizing the update for the machine learning model includes privatizing the update using separated differential privacy, wherein privatizing the update using separated differential privacy includes:

decomposing the weight vector into the unit vector and the magnitude.

3. The non-transitory machine-readable medium as in claim **2**, wherein the magnitude is privatized using relative noise.

4. The non-transitory machine-readable medium as in claim **2**, wherein the unit vector and the magnitude are each differentially private.

5. The non-transitory machine-readable medium as in claim **4**, wherein the magnitude is privatized with absolute error.

6. The non-transitory machine-readable medium as in claim **4**, wherein the magnitude is privatized with relative error.

7. The non-transitory machine-readable medium as in claim **4**, wherein the unit vector is privatized based on ℓ_2-unit vectors on a unit cube.

8. The non-transitory machine-readable medium as in claim **4**, wherein the unit vector is privatized based on ℓ_∞-unit vectors on a unit cube.

9. The non-transitory machine-readable medium as in claim **1**, wherein the machine learning model is a natural language processing model, an image classification model, or a voice classification model.

10. The non-transitory machine-readable medium as in claim **9**, additionally comprising receiving an updated machine learning model from the server at the client device, training the updated machine learning model using local data at the client device, and transmitting a privatized update for the updated machine learning model to the server.

11. A data processing system comprising:

a memory to store instructions;

one or more processors to execute the instructions, wherein the instructions cause the one or more processors to:

receive a machine learning model from a server at a client device;

train the machine learning model using local data at the client device to generate a trained machine learning model;

generate a weight vector by subtracting first weights of the received machine learning model from second weights of the trained machine learning model;

generate an update for the machine learning model, the update including the weight vector;

privatize the update for the machine learning model by separately privatizing a magnitude and a unit vector of the update; and

transmit the privatized update for the machine learning model to the server.

12. The data processing system as in claim **11**, wherein to privatize the update for the machine learning model includes to privatize the update using separated differential privacy, wherein to privatize the update using separated differential privacy includes to:

decompose the weight vector into the unit vector and the magnitude.

13. The data processing system as in claim **12**, wherein the magnitude is privatized using relative noise.

14. The data processing system as in claim **12**, wherein the unit vector and the magnitude are each differentially private.

15. The data processing system as in claim **14**, wherein the magnitude is privatized with absolute error.

16. The data processing system as in claim **14**, wherein the magnitude is privatized with relative error.

17. The data processing system as in claim **14**, wherein the unit vector is privatized based on ℓ_2-unit vectors on a unit cube.

18. The data processing system as in claim **14**, wherein the unit vector is privatized based on based on ℓ_∞-unit vectors on a unit cube.

19. The data processing system as in claim **11**, wherein the machine learning model is a natural language processing model, an image classification model, or a voice classification model.

20. The data processing system as in claim **19**, the one or more processors additionally to: receive an updated machine learning model from the server at the client device; train the updated machine learning model using local data at the client device; and transmit a privatized update for the updated machine learning model to the server.

21. A method comprising:

receiving a machine learning model from a server at a client device;

training the machine learning model using local data at the client device to generate a trained machine learning model;

determining a weight vector that is a difference between first weights of the machine learning model and second weights of the trained machine learning model;

generating an update for the machine learning model, the update including the weight vector;

privatizing the update for the machine learning model by separately privatizing a magnitude and a unit vector of the update; and

transmitting the privatized update for the machine learning model to the server.

22. The method as in claim **21**, wherein privatizing the update for the machine learning model includes privatizing the update using separated differential privacy, wherein privatizing the update using separated differential privacy includes:

decomposing the weight vector into the unit vector and the magnitude.

23. The method as in claim **22**, wherein the magnitude is privatized using relative noise.

24. The method as in claim **22**, wherein the unit vector and the magnitude are each differentially private.

25. The method as in claim **24**, wherein the magnitude is privatized with absolute error.

26. The method as in claim **24**, wherein the magnitude is privatized with relative error.

27. The method as in claim **24**, wherein the unit vector is privatized based on ℓ_2-unit vectors on a unit cube.

28. The method as in claim **24**, wherein the unit vector is privatized based on ℓ_∞-unit vectors on a unit cube.

29. The method as in claim **21**, wherein the machine learning model is a natural language processing model, an image classification model, or a voice classification model.

30. The method as in claim **29**, additionally comprising receiving an updated machine learning model from the server at the client device, training the updated machine learning model using local data at the client device, and transmitting a privatized update for the updated machine learning model to the server.

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